

Real-time adaptive automation system based on identification of operator functional state (OFS) in simulated process control operations

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Abstract

This paper proposes a new framework for the on-line monitoring and adaptive control of automation in complex and safety-critical human-machine (HM) systems using psychophysiological markers relating to humans under mental stress. The starting point of this framework relates to the assessment of the so-called operator functional state (OFS) using psychophysiological measures. An adaptive fuzzy model linking Heart-Rate Variability (HRV) and Task Load Index (TLI) with the subjects' optimal performance has been elicited and validated off-line via a series of experiments involving process control tasks simulated on an automation-enhanced Cabin Air Management System (aCAMS). The elicited model has been used as the basis for an on-line control system via the predictions of the system performance indicators corresponding to the operator stressful state. These indicators have been used by a fuzzy decision-maker to modify the level of automation under which the system may operate. A real-time architecture has been developed as a platform for this approach. It has been validated in a series of human volunteer studies with promising improvement in performance.

Index Terms: Man-machine Systems, Adaptive Automation, Operator Functional State, Psychophysiology, Neural-Fuzzy Modeling and Control, Signal Processing, Genetic Algorithms.

I. INTRODUCTION

In safety-critical and automation-enhanced human-machine (HM) systems the operator is required to continually adapt to new and unforeseen changes in the dynamic process under control. This includes determining whether and what actions are required to prevent or correct for drifts or faults emanating from the environment under control [1]. The allocation of functions between agents within HM systems has become more complex with increasing and dynamic operational demands and potential operator stress and fatigue, with a consequent threat to safety and reliability [2]. Despite the widespread benefits of automation, there are also well-documented problems for operator effectiveness [3], often attributed to ‘clumsy automation’, where humans are left only with the tasks which are too difficult (or too expensive) to automate. More recent developments acknowledge advantages of ‘human-centred’ solutions [4] with systems being adaptive in that the capabilities and limitations of both machine and human are considered as linked elements in a dynamic sharing of task demands [5]. This may be addressed by applying control changes dynamically between human and machine in response to changing resources or needs of the two agents to assure system safety. Although the best way of function allocation between human and machine is assumed to be dynamic [6, 7], relevant criteria still remain unclear for decisions about when or what to adapt, how to infer, and who should decide [8], as well as for establishing reliable and valid predictors for these criteria.

Recent efforts in the promoting an assessment of the operator functional state (OFS) have been aimed at the prevention of manifest HM system performance breakdown in complex tasks [9, 10]. According to an OFS framework [11, 12] system performance is assumed to be influenced by human-task interaction and underlying cognitive, energetic and subjective processes in the regulation of human performance. On the one hand, these processes facilitate protection of top level task goals by compensatory (effort-allocation) strategies. On the other hand they attract costs

in the form of ‘latent decrements’ such as the use of risky strategies and increasing physiological activation [11], leading eventually to manifest breakdown under extreme task demands. It is assumed that the detection of the development of vulnerable (high-risk) operational states (where operators are still able to manage predictable demands but not necessarily unexpected or difficult problems) would allow for prediction of periods of increased operational risk and prevent serious HM system failure. A solution for controlling the risk of potential performance breakdown can be in the integration of adaptive automation concepts especially those designed for maximising human task involvement, while protecting system performance against compromised Operator Functional States (OFS). As a result, Adaptive Automation (AA) should enable switching task allocation dynamically between human and machine in response to changing resources or needs of the two agents to assure system safety [13].

In research studies compromised operator states are often described in terms of differences between low and high workload conditions, with switching control away from the human operator whenever a ‘high workload state’ is detected [14]. However, in OFS assessments, and with regard to the development of high-risk states, it seems promising to explore the effect of monotonically increasing task load—from situations in which integrity of central aspects of task performance can be maintained, until compensatory control limits are reached and primary task performance begins to fail. Based on stress-strain testing methods used in mechanical engineering, a loading phase is followed by an unloading phase with monotonic reduction of task load until performance recovers to within normal limits. This ‘cyclic loading’ method has already been successfully used for the detection of compensatory control strategies using subjective ratings and performance measures [12, 15]. Results for primary and secondary performance measures and ratings on effort, anxiety, and fatigue provide some consistency with studies on process control operations in similar environments but addressing different questions [16, 17]. Because of specific advantages of psychophysiological measures (e.g., relatively unobtrusive, with continuous data acquisition even

in absence of apparent behaviour; [18-20]), they are particularly strong candidates, in combination with others, for an indication of OFS. Most of these measures can be continuously acquired at high sample rates and therefore may allow for coarse-grained as well as fine-grained analyses of mental processes involved. They may reflect changes in mental processes even before they become manifest in task performance, or when changes in subjective states are felt.

Besides studies using pure task performance based criteria for triggering shifts in the level of automation [21], a growing number of studies emphasise the measurement of psychophysiological measures in the context of adaptive automation [14, 22, 23]. While most studies rely on either performance or psychophysiological measures in the present context, an amalgamating approach is seen as most appropriate for executive control processes underlying the regulation of human task performance. Autonomous nervous system activity, notably the 0.1 Hz component of heart rate variability, has been found to respond reliably to changes in mental effort [24], particularly in simulated operational settings where executive problem solving is involved [25], and has already been applied to simulated process control environments [22, 23]. Executive control or function is seen as a major determinant in the regulation of human performance in dynamic and complex task environments since they refer to cognitive processes such as flexible use of attentional and planning strategies, problem-solving, reasoning and decision-making [26, 27]. As these processes are assumed to be mediated by the prefrontal cortex, central nervous system measures such as frontal midline theta activity and the 'task load index'(TLI) [28-30] have been found to reflect load manipulations in complex task environments [31, 32, 33].

Real-time data acquisition and analysis of necessarily multiple variables for OFS assessment provide scope for the identification of early stage evidence for performance breakdown. Transitions in OFS can be assumed to be smooth but reflected by different changes within state marker patterns. The criteria for state identification must therefore allow for the overlapping classification of states as facilitated by e.g. fuzzy logic based methods. Triggering shifts in

automation of the human-machine system will, therefore, be based on fuzzy-based OFS identification, thus enabling the closing of the loop for AA. An adaptive automation system acquires task performance and psychophysiological data, on-line analyses the acquisitions to produce OFS markers, and manages task allocation between human and machine.

The aim of the paper is (1) to present results of a simulation study based on off-line data acquisition, analysis, and modelling; (2) to highlight the central role of a system for real-time monitoring and control within an integrative framework for the components in a closed-loop system for adaptive control of automation; (3) to outline the functionalities of its subcomponents based on off-line and on-line data analyses; (4) to describe the comprehensive studies for integrating interlinked components into on-line processing; (5) to construct an AA control system based on a psychophysiological fuzzy model; and (6) to validate the system in human real-time studies.

II. BASIC EXPERIMENTAL SETUP

A. Automation Tasks

The automation-enhanced (aCAMS) simulator [34], which is the modified version of the Cabin Air Management System (CAMS) [16, 35, 36], served as a representative process control environment. This semi-automatic system makes major executive demands on the operator's mental resources and requires operators to interact with a dynamic visual display, which provides data on system variables and functions via a range of controls and automation tools. The main task of the operator is to monitor the performance of the automatic controllers and to maintain an appropriate quantity and quality of breathable air within e.g. a space capsule, if there is a divergence from a safe system state (see Fig.1). This can be accomplished by keeping key system parameters (oxygen (O₂), cabin pressure, carbon dioxide (CO₂), temperature, humidity) within their respective

normal operating ranges (primary task), to maintain a healthy environment. These parameters are initially controlled automatically. But when failure occurs within the automatic control of any of the previous parameters, manual control is needed by an expert operator. The operator, who can normally read the gauges on the sensors, needs to diagnose the origin of the system disturbance by carrying out suitable tests. Once the operator has identified the system's fault, the latter can be repaired by means of the maintenance facility. Each system parameter has its own automatic process controller and a predefined normal, transition, and error range and as a result, secondary tasks such as alarm acknowledgement and tank level recording are normally incorporated. The alarm acknowledgement task required operators to confirm alarms as soon as possible, thus providing inherently a measure of Alarm Reaction Time (ART). The Tank Level Recording (TLR) task requires the operator to maintain a precise electronic record of the current oxygen tank level every minute. In addition, subjective state measures of anxiety, effort and fatigue are taken via on-screen visual analogue scales.

In the present study, aCAMS was used in a simplified version with no fault management required but was set up for an increasing and decreasing number of key system parameters to be manually controlled, with the remaining loops under automatic control. A cyclic-loading schedule of nine consecutive 15-min task periods was applied, with the level of manual control load increasing stepwise from one to five (loading phase) and then decreasing from five back to one (unloading phase). The aim was to force instability and dysfunction in mental task performance, usually protected by compensatory control processes [11], allowing the detection of near-breakdown periods of OFS, and analysis of recovery from dysfunctional strain during unloading phases.

B. Participants and Experimental Procedure

Prior to formal data-acquisition experimental sessions, each subject (all subjects were researchers and PhD students recruited from the University of Sheffield, UK) was trained on the manual process control task for over 10 hours so that they became familiar with the aCAMS environment and the simulated control tasks.

After the training sessions, a total of 11 healthy subjects were selected for the formal experiments and each of them worked for two sessions, each session lasting about 2 hours. The sessions for each participant were performed at the same time of the day in order to avoid circadian effects [37]. Immediately after completing the health questionnaire and subjective ratings, the subject started process control operations. Each process control condition lasted for 10 min and was interrupted by completing subjective ratings for about 20 s. The performance data were recorded in synchrony with process control operations.

C. Data Acquisition and Analysis

Preliminary assessments of OFS were based on sessions of 8 x 15 min task segments of which the first four tasks had incremental levels (levels 1, 3, 4, 5) while the following four tasks had decremental levels (levels 5, 4, 3, 1) of the manual control load. The number associated to the task level denotes the number of parameters to be controlled at a time.

1) The aCAMS data acquisition:

The levels of key performance parameters were sampled at 1 Hz by aCAMS, logged into file and classified as system parameters either within normal operational range (TIR), or in transient (SIT) range or in error range (SIE) according to the aCAMS simulation model and to assumed requirements of air quality for a cabin crew. The system performance measures of the primary task were taken to be the percentage of time that any of the key parameters was in normal, in transient

or in error range. Secondary task performance parameters were sampled at occurrence (false alarms for Alarm Reaction Time- ART were randomly presented at approximately every 30-s interval; TLR were taken at 60-s intervals). Subjective ratings were presented at 15-min intervals corresponding to the next-task shifts. Primary and secondary performance parameters and subjective ratings were extracted from the log files and off-line analysed using purpose-built programmes to obtain the corresponding measures.

2) *The ECG and EEG data acquisition:*

The Active Two System[®] (BioSemi, The Netherlands) was used for continuously acquiring psychophysiological signals of 'the electrocardiogram (ECG), electrooculogram (EOG), the electroencephalogram (EEG)'. For EEG, the standard Fz, AFz, Pz, CPz and POz signals were identified on a 64 sites head-cap arranged in the 10-20 system [38], the vertical and horizontal EOG were used for ocular artefact correction of the EEG, and the left and right mastoids for referencing EEG signals. Data were sampled at 2048 Hz and controlled via ActiView 5.33 software (BioSemi, The Netherlands), which enabled the experimenter to monitor signal acquisition, to save psychophysiological and marker signals in BioSemi-Data-Files (BDF format) for off-line analysis and to allow for setting-up data transmission via TCP/IP.

Psychophysiological signals were analysed using the "Brain Vision Analyzer[®]" (Brain Products, Germany) procedures for EEG and ECG off-line analysis. The LabVIEW (National Instruments, USA) virtual instruments as already used in [39] were applied in this study to obtain heart rate and HRV. Both psychophysiological measures were further processed and edited for statistical data analysis using MS-Excel (Microsoft, USA) programs.

III. MODELLING OF OPERATOR FUNCTIONAL STATE (OFS)

A. Analyses of OFS Variables

Both autonomic and brain measures can be considered as potential markers of strain. Cardiovascular (CV) indices, mainly heart-rate (HR) and heart-rate-variability (HRV), derived from power spectrum analysis of the cardiac interval, have been found to respond to changes in workload and mental effort [40]. In particular, it can be represented by two types of indicators, HRV1 and HRV2. On the one hand, HRV1 defines the HRV factor which represents the 0.1 Hz component of the HR signal. Therefore, HRV1 is calculated by averaging the power spectrum of the HR signal collected within a period of 7.5 min (half task duration) in the frequency range from 0.07 Hz to 0.14 Hz [37]. On the other hand, HRV2 is considered as the ratio between the standard deviation over the mean value of the HR signal within a time period of 7.5 min.

A more reliable marker is the Task-Load-Index (TLI) identified by Gevins and his group [41]. TLI is based on the presence of high levels of theta (θ) activity at frontal midline sites, with concomitant attenuation of alpha (α) power in parietal sites [theta/alpha]. Observation of reduced frontal-midline theta power may reflect direct effects of fatigue or strategic disengagement from the executive requirements of the task management [32] and is defined by two formulas, TLI1 and TLI2 as follows:

$$\left\{ \begin{array}{l} TLI_1 = \frac{P_{\theta, Fz}}{P_{\alpha, Pz}} \\ TLI_2 = \frac{P_{\theta, AFz}}{P_{\alpha, CPz \cdot POz}} \end{array} \right. \quad (1)$$

where P_{θ} and P_{α} refer to theta- and alpha-band power, respectively.

$P_{\theta, Fz}$ and $P_{\theta, AFz}$ are the θ activities of Fz and AFz electrodes respectively. The θ activity was calculated by averaging the power spectrum of the θ frequency range (4-7.5 Hz). Similarly, $P_{\alpha, Pz}$ and $P_{\alpha, CPzPOz}$ are the α activities of Pz and the pool of CPz and POz electrodes, respectively. The α activity was calculated by averaging the power spectrum of the α frequency range (8-12.5 Hz) [42].

Repeated analyses of variance using the General Linear Model (GLM, ANOVA) procedure of the SPSS software (SPSS Inc., USA) were computed for each measure to assess effects in the experimental sessions, each containing the levels of manual control load (i.e. 1, 3, 4 or all 5 key parameters controlled manually) for each phase of loading and unloading. Analyses were computed separately for primary and secondary performance variables, the subjective ratings and the psychophysiological variables HRV and TLI.

Task performance: For the monitoring and control activities the operators maintained aCAMS parameters in their respective ranges for more than 95 % of the time on average. However, there is evidence of a performance breakdown when all five parameters were manually controlled with a drop in TIR to 90 % only. Results of the repeated-measures ANOVA on these data revealed a main effect for manual control load ($F[3,3] = 49.5$, $p = 0.005$). The secondary task performance measures also showed evidence of impairment under a high load. Although there was monotonic increase in ART with increases in manual control load, differences were not significant. However, the time delay in TLR increased with increasing manual control load ($F [3,3] = 7.5$, $p = 0.066$). According to the task performance parameters, the HM system was in a vulnerable state or at least close to it in the high loading conditions, where 4 or 5 out of 5 key parameters were to be controlled manually.

Among the subjective state reports, the anxiety rating resulted in significant differences for the task load conditions, indicating that the operators felt tenser for higher levels of load. Subjective

fatigue showed a significant increase across all conditions of the loading and unloading phases and, therefore, seems to reflect time-into-session effects as expected. Though it was expected that the effects for level of load and time-into-session would be reflected in the amount of effort spent, in fact, no significant effect was evident.

Psychophysiology: There was a significant continuous decrease in heart rate from one condition to the next, indicating a deactivation process during the session. For the 0.1 Hz component of HRV (HRV1) there was evidence of a variation consistent with the levels of manual control load imposed on an individual level, although this did not reach a level of statistical significance. Focused attention or executive control as assumed to be reflected by TLI2 systematically co-varied with the levels of load, i.e. the operator demand on executive control activities increased with increasing manual control load ($F [3,3] = 9.7, p = 0.047$; see Fig.2). The TLI2 increased during the loading phase and proceeded to a lower level during unloading. This appears to reflect differences in executive control demands according to variations in manual control load and time on task because of accumulated fatigue.

B. Fuzzy Modelling

For the purpose of modelling, fuzzy logic [43] was chosen as the main paradigm for characterizing the input/output mappings because of its tolerance to uncertainties and also for the fact that it can model human perception in a transparent (interpretable) way without any significant loss in accuracy. In this study, two types of adaptive fuzzy models were comparatively employed to process the modelling phase. The most popular fuzzy rules processing techniques are the Mamdani- [44] and Takagi-Sugeno (TSK) (ANFIS structure) types. The ANFIS and the Mamdani based models were tuned via hybrid learning [45] and Genetic Algorithms (GA) [46], respectively.

The optimal MF parameters (mean, μ , and standard deviation, σ) were determined when the learning or optimisation process reached the minimum of Mean-Squared-Error (MSE) defined by the following equation:

$$MSE = \frac{1}{N} \sum_{k=1}^N [y(k) - y_M(k)]^2 \quad (2)$$

where $y(k)$ is the actual output, $y_M(k)$ is the calculated model output at the sampling instant k , and N is the number of samples.

In order to carry out this modeling operation successfully it was important to first specify the variables associated with this input/output mapping and then carry out the real-time experiments [47]. Our modelling results suggested the use of the Mamdani-type fuzzy model instead of the TSK-based model, because of the higher transparency and the adequate accuracy of the former. HRV1 and TLI2 were found to be most sensitive to the changes in mental workload [40, 42, 48], therefore they were chosen as the model inputs and the model output is represented by the percentage Time-in-Range (TIR).

Prediction of Time-in-Range (TIR): The Mamdani-type fuzzy model takes HRV1 and TLI2 as the inputs and produces TIR as the output. A fuzzy rule-base was generated in accordance with an understanding of the psychophysiology of human beings in response to various levels of mental stress. This was built with the aid of an expert from the Sheffield University Department of Psychology. The proposed rule-base was basically derived from a theoretical point of view, however, it does not mean that highly complex real world systems such as those encompassed by humans always stick to these theoretical assumptions. Hence, a premise firing weight is added to each rule to account for subject variability. A fuzzy rule can read as follows:

IF (HRV1 is M) and (TLI2 is S) THEN (Time-in-Range is H) (with a premise firing weight)

A premise firing weight is added to each rule to account for subject variability. For each individual subject's model, this weight represents the amount of strength of a rule among other rules during the inference mechanism. This is because the models were assumed to be subject-dependent, i.e. in this way all models have the same rule-base but with different rule-weights.

Table I shows the complete fuzzy rule-base. The 'S', 'M', 'B', 'VB', 'L', 'H', 'VH' denote small, medium, big, very big, low, high, and very high, respectively. The blank cells in the rule-base table means that the combination of the premises is not applicable.

In this study, the signal data sampling-interval was taken to be 7.5 min and Gaussian membership functions (MF) were used for all fuzzy sets. The MFs parameters (μ , σ) and the rule firing weights were optimized using Genetic Algorithms. The fuzzy predictor truncates the degree of the input memberships, infers the inputs with the correlation-minimum method and then scales the result with the rule firing weight to obtain an output fuzzy set. A TIR prediction is obtained by passing the fuzzy output set to the centroid defuzzification algorithm. Fig.3 shows an example of the model prediction. The model was trained and validated using two sets of normalised data from 'Session 1' and 'Session 2', respectively.

Prediction of System-in-Error (SIE): TIR should provide information only on the possibility that the system may deviate from the normal operating range. The time that the system operation is outside the in-range band is more relevant for triggering the adaptive mechanism. A “System-in-Transition” (SIT) indicator is hence included to indicate that the system operation is transitional before getting into an “abnormal” state (error). Thus, a fuzzy predictor was constructed using the TIR (predicted) and SIT (from aCAMS) as the inputs to generate “System-in-Error” (SIE) prediction. The SIE predictor is represented by a Mamdani-type fuzzy model with three equally

distributed Gaussian-type membership functions and its rule-base is shown in Table II. The manipulation of the SIE predictor used the same procedures as the TIR prediction but without the rule firing weights. Fig.4 shows the SIE prediction corresponding to Fig.3. There is an offset in the prediction. In practical application, the offset can be eliminated by assigning a threshold value. Hence, the prediction should lead to an all-or-none “error” signal.

IV. REAL-TIME ADAPTIVE AUTOMATION SYSTEM

A. System Architecture

The ultimate goal of the study undertaken is to close the control loop, i.e. operation allocation of a human-machine system with OFS as the feedback signal. Hence, a real-time system has been developed to provide a platform for adaptive control of automation through OFS monitoring. Fig.5 shows the architecture of the real-time framework in the context of possible spacecraft management control from an earth station.

B. Closed-loop Control of Adaptive Automation

The proposed closed-loop model is shown in Fig.6 which employs the aCAMS-based simulator as the controlled process, integrates the currently used off-line analysis approaches and the adaptive fuzzy modelling as the OFS inference engine, and is equipped with an artificial intelligent control engine for function allocation of the human-machine system.

Via the simulation results (Fig.3 and 4), the models (Fuzzy Model Predictors (1) and (2)) showed a capability of effectively exploiting the information contained in the measured physiological and performance data. The model output, “System-in-Error”, as shown in Fig.4, provides bio-feedback predictions to foresee the time that the system may be in conditions of drifts or faults. Thus, system operation can be re-allocated between human and machine to assure operation performance and

system safety. Fig.6 shows the control system schematic with OFS prediction and primary task performance for immediate feedback correction. The AA system takes electrophysiological measurements (EEG and HR via the BioSemi Active Two System) together with the process performance (from aCAMS) to infer the adequate automation control actions to aCAMS (see Section C for implementation). This function of the AA system is only to assist the operator in process performance maintaining by adapting to the operator's physical and mental states. In other words, the design is actually a regulator problem with the aim of maintaining the aCAMS process performance at an acceptable level which assures a healthy environment in the cabin.

During the real-time experiments, scaling factors adjustment for HRV1 and TLI2 was mandatory. Therefore, before the formal experiment a factor-adjustment experiment was conducted for this purpose.

The OFS analyser processes the psychophysiological responses to provide information of how the system may drift into 'error'. These responses were processed by calculating the moving average of a 128 s window width and 1 s shift. Once a possible system abnormality is foreseen, the LOA Reallocator switches system operation from human (manual) to machine (automatic) and increases the level of automation (LOA) by one step (a sub-process of aCAMS). The LOA value is proportional to the OFS and hence it is considered as an indicator of the amount of the operator stressful state. A "System-in-Error" reported by aCAMS represents an anticipated system catastrophe if the system operation is not immediately corrected. The occurrence of such a fault elicits the LOA Reallocator for immediate automation intervention. This feedback correction is synchronised with aCAMS, 1 s in this case. Once an error occurs, the control utilizes a hysteresis loop which imposes a refractory duration (150 s) to LOA commands to avoid adverse chattering effect. This coordinating scheme assures function allocation between human and machine for persistent system safety and operation performance. If there is no reported or predicted error, the level of automation is reduced by one degree.

C. System Implementation

Fig.7 shows the functional blocks of the developed real-time adaptive automation system. OFS monitoring and control, aCAMS simulation, and psychophysiological data acquisition are distributed across 3 independent computers. The system was implemented with MFC (Visual C++ 8.0, Microsoft, USA) on a Window-XP computer. The two peripheral computers communicate with the control system through Ethernet networking using the TCP/IP communication protocol, in an either intra- or inter-networking environment.

For aCAMS it was necessary to extract the relevant information relating to the OFS variables together with implementation of the functionality to continuously transfer/log the information on monitoring and control operations via TCP/IP. Psychophysiological responses from BioSemi[®], which were previously off-line analysed with several purpose-built programs, were processed with the procedures described in the subsequent section. This platform performs on-line acquisitions from both aCAMS and BioSemi and simultaneously carries out the analyses in real-time.

D. Inference Procedures

The inference engine shown in Fig.7 was used for analysing the task performance (from aCAMS) and the psychophysiological (from BioSemi[®]) data. The data analysis includes the following procedures:

- 1) Acquire the task performance and psychophysiological data from the two peripheral computers using TCP/IP networking. Extract the performance channels and compute the Time-in-Range (TIR) measures;

- 2) Extract the ECG channels, compose the ECG signal, detect the R-peaks and transpose inter-beat intervals into equidistant sinusarrhythmia time-series;
- 3) Extract the EEG channels and re-reference all signals via the mastoid signals;
- 4) Filter the EEG signals using a band-pass filter from 1.6 Hz to 25 Hz;
- 5) Select the EEG signals from the appropriate channels such as Fz, Pz, AFz, CPz, and POz;
- 6) Partition the selected EEG channels into 2-s segments;
- 7) Detect the artefacts by identifying the EEG channel amplitudes out of $\pm 100 \mu\text{V}$ range per segment; data in this segment will be ignored in future analysis;
- 8) Calculate the power spectrum for the selected EEG channels and ECG sinusarrhythmia;
- 9) Extract the associated frequency ranges as specified for the EEG and ECG variables;
- 10) Derive the OFS markers (HRV1 and TLI2) based on the above psychophysiological data.

E. Experimental Results

A series of two-session experiments was performed on 9 out of 11 subjects. Each session contained 3 conditions (40 min each). In the first session, 'Condition 1' used the fuzzy logic TIR predictor with its psychophysiological and SIT inputs in conjunction with the SIE measurements to perform AA (see Fig.6). Under 'Condition 2', SIE alone was used in the LOA switching regime. For 'Condition 3' the same procedure as for 'Condition 1' was adopted, to determine if there was any change in performance from the initial baseline. For 'Session 2' (held some weeks later), the SIT signal that has been used in 'Session 1' trials was removed from conditions 1 and 3.

The main logged variables are shown graphically for 'Participant 1' in Fig.8. Fig.8a shows the moving average version of the 2 psychophysiological variables HRV1 and TLI2. The next trace (Fig.8b) gives the moving average of SIT signal used for the real-time fuzzy logic TIR prediction. Fig.8c indicates the error performance, particularly when the system switched automation level

because of the error exceeding the set threshold level of 0.1. The bottom trace (Fig.8d) shows how the level of automation (LOA) was adjusted throughout this 'Condition 1' trial. It can be seen that adjustments were made via 3 psychophysiological switches and 3 error switches. Fig.9 shows the equivalent results for 'Condition 2' when only SIE (from aCAMS) was used for adaptation. In this case, there were 6 switches made, but the LOA adjustments were made around a lower average LOA than in Fig.8d, with the resultant larger error conditions as seen in Fig.9c.

Equivalent results are shown in Fig.10 and Fig.11 for 'Participant 11'. Under 'Condition 1' with the fuzzy logic TIR predictor active, the system never went into error because the LOA was kept at a high value. In this case, the TIR predicted (sampled) and actual TIR (logged from aCAMS over time) shown in Fig.10c demonstrates reasonable correlation, indicating that the TIR fuzzy rule base is sensible. For 'Condition 2' (Fig.10) without the TIR predictor, the system went into undesirable error switching on several occasions. It can be seen that this is because the LOA was often at too low level. An improved performance under AA with psychophysiological switching is seen in Fig.12 for 'Condition 3' for 'Participant 11'.

The individual statistical results for the 3 conditions trials for 'Session 1' are shown in Tables III-V. Analyses of these results for both sessions are given in Tables VI and VII. From these later tables it is seen (for 'Session 1') that the inclusion of the full TIR prediction gave lower mean transients, resulting in lower mean errors, lower SIE shifts in LOA and thus leading to higher mean and standard deviation LOA. The same overall performance was obtained during 'Session 2' trials. All operators showed some advantages of the adaptive controller with reduction in the system error. A second strong effect was a reduction in the number of control actions for all participants, and was a direct effect of the increased shift to higher levels of average LOA under the full fuzzy logic regime.

V. DISCUSSION AND CONCLUSIONS

The first part of this work was related to elicitation of linguistic fuzzy-type models for identifying OFSs using psychophysiological and performance measures. Model analyses revealed that the GA-based Mamdani-type model generalised better across the data used and that HRV1 and TLI2 represented the best correlating inputs to the performance output “Time-in-Range”. The predicted “Time-in-Range” together with the “System-in-Transition” (from aCAMS) produces a “System-in-Error” that is used to switch the operation mode between human and machine. The model represents a concise, transparent (easily understandable) and robust characterization of OFS and can be easily extended or modified to accommodate additional input variables, membership functions, and fuzzy rules. The identification of these OFSs paved the way for proposing a new framework of real-time monitoring and adaptive control of automation in complex and safety-critical human-machine systems.

The performance data and the subjective ratings provide some consistency with the studies on process control operations in similar environments where psychophysiological measures were not used [16]. Results for the psychophysiological markers, especially the EEG activity at specific cortical regions, are comparable to those obtained from simulated flight environments with different levels of workload [49]. The OFS markers, as they are used in the closed-loop system, allows adaptive control of automation of the process control environment, and provide a valid and reliable basis for triggering shifts in control of the human-machine dialogue.

Real-time experimental studies using aCAMS, the OFSs predictor, and the LOA fuzzy decision-maker have shown that successful switching of system automation is possible. It is worth noting that in all experiments the LOA fuzzy decision-maker responded adequately to incoming inputs. The real-time experiments involved most of the volunteers who partook in earlier experiments and their data were used for off-line modelling. Since the aim of the fuzzy logic

adaptive controller was to predict and guard against error-prone states, tests were carried-out by comparing it against a baseline in which an increase in automation was triggered by system error.

Statistical results showed generally enhanced performance for the adaptive controller, over an error-triggered system, including reduced error, improved secondary task performance and reduced subjective strain. This pattern was especially true for the combined OFS in conjunction with SIT model.

However, the authors of this paper are aware that the human present state of knowledge that acts as a foundation for the adaptive controller is quite limited. One needs indeed further information in at least two areas if one is to improve on the modest successes so far achieved. First, while the fuzzy modelling in the present study was based on normative accounts of psychophysiological variables, it is clear that there are marked differences between individuals that may not be readily resolved by adjusting weights alone. The authors of this paper are currently exploring the use of fuzzy clustering techniques [18] to capture individual response idiosyncrasies more directly, and thus provide a more valid basis for adaptive control. Second, a major issue concerns the interpretation of TLI changes, in particular the attenuation sometimes seen at high loads. The OFS framework leads us to predict both that TLI will increase with high loads (with increased effort) and also that TLI will decrease when effort leads to fatigue. A low level of TLI is, thus, in itself ambiguous; load may be low, effort has not been engaged, or fatigue has occurred. New ways to disambiguate these possibilities to further enhance the real-time adaptive controller are also currently being explored.

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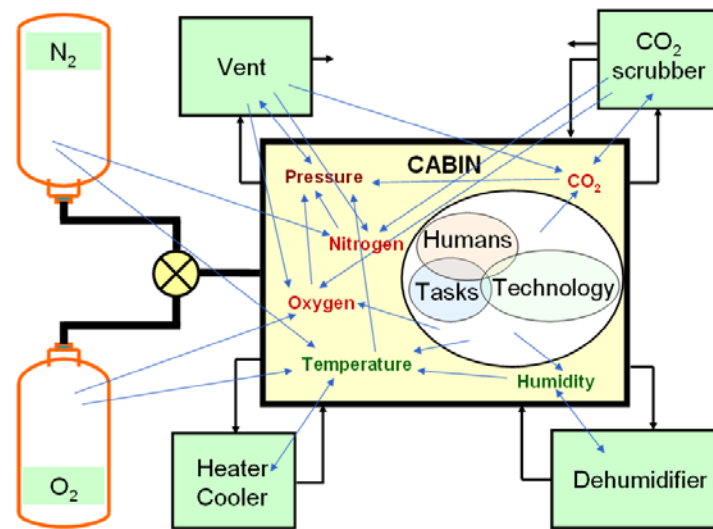


Fig.1. Model of interacting technical subsystems for cabin air management. The arrows indicate interdependencies between subsystems and air parameters.

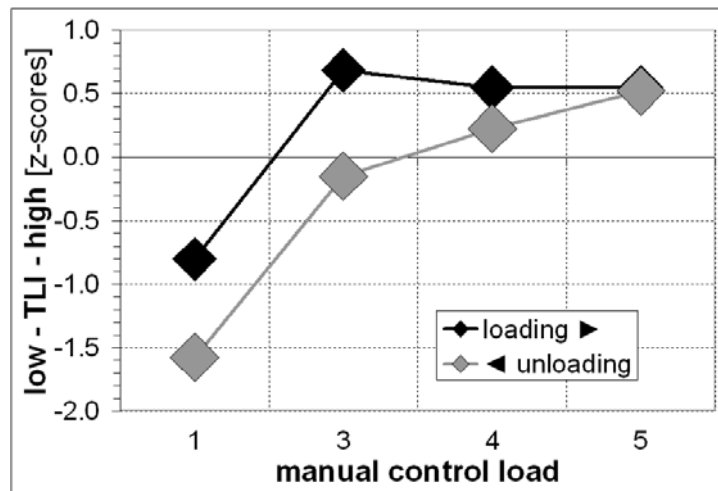


Fig.2. Task load index (TLI2) aggregated over all sessions and participants.

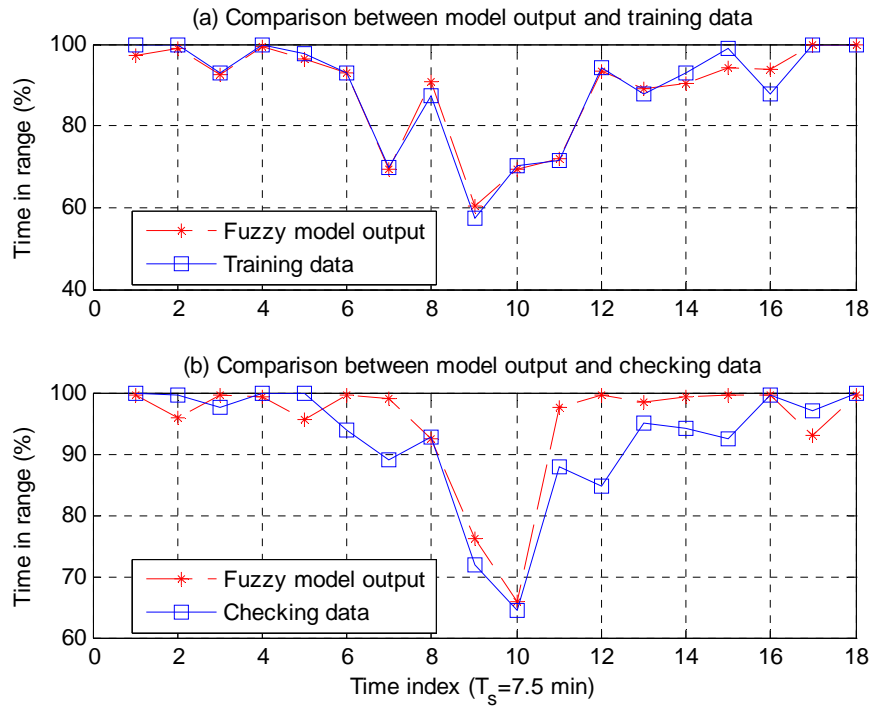


Fig.3. TIR prediction by the Mamdani-type fuzzy model with GA-optimized MFs and rule weights.

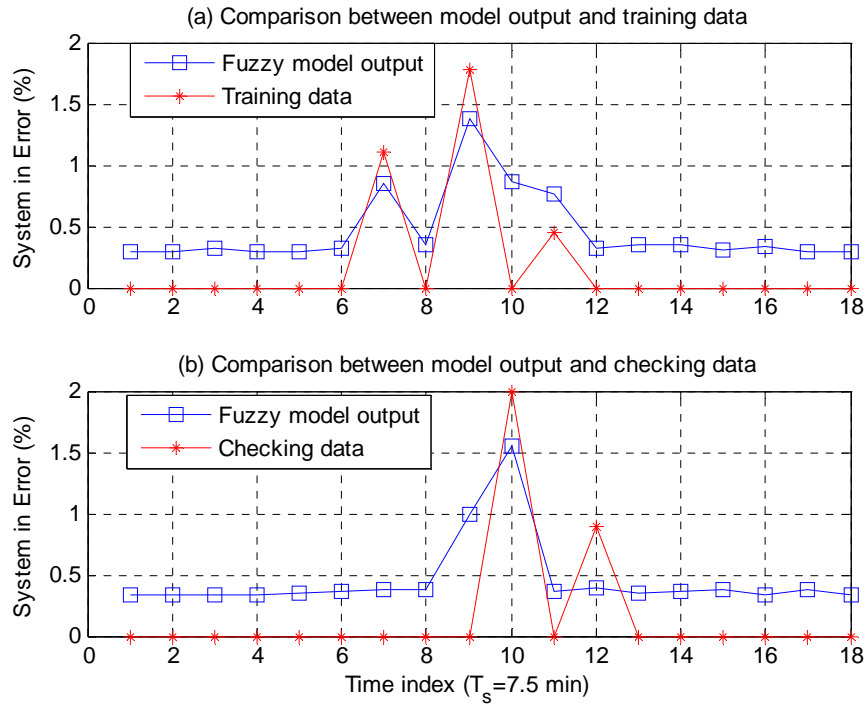


Fig.4. SIE prediction via the Mamdani-type fuzzy model.

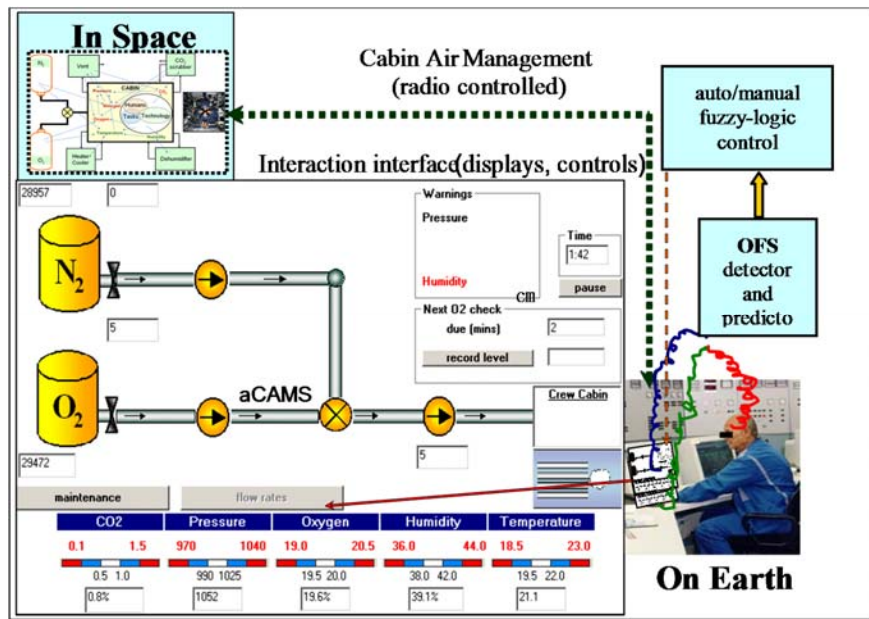


Fig.5. Schematic of a closed-loop system for fuzzy-logic based adaptive control of cabin air management through operator functional assessment.

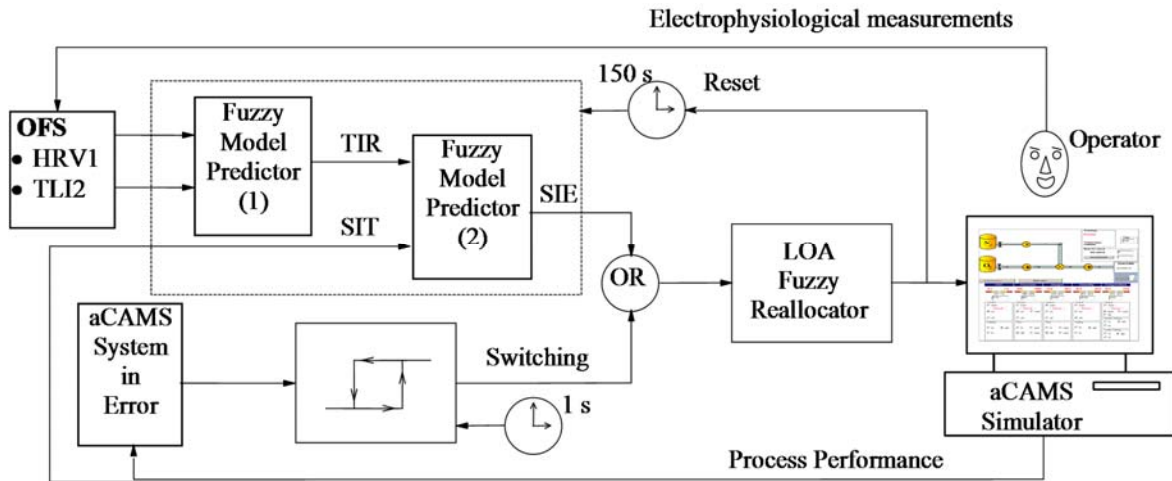


Fig.6. The control system of adaptive automation with OFS prediction and process feedback.

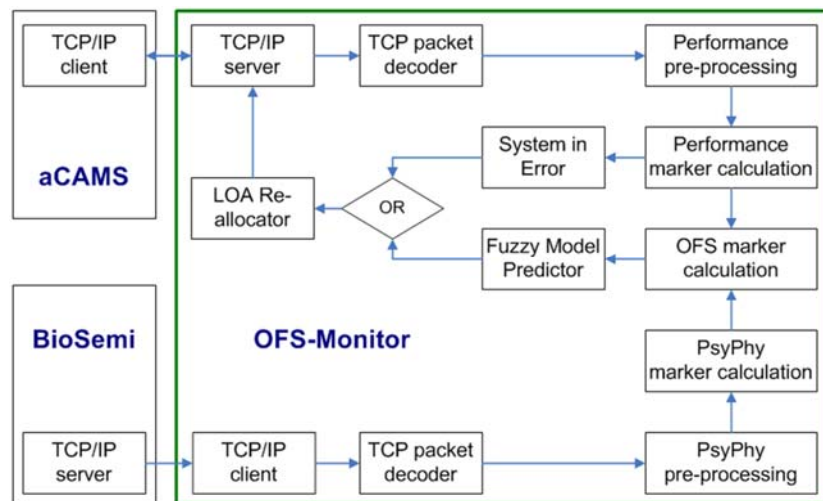


Fig.7. Schematic of a closed-loop system for fuzzy-logic based adaptive control of cabin air management through operator functional assessment.

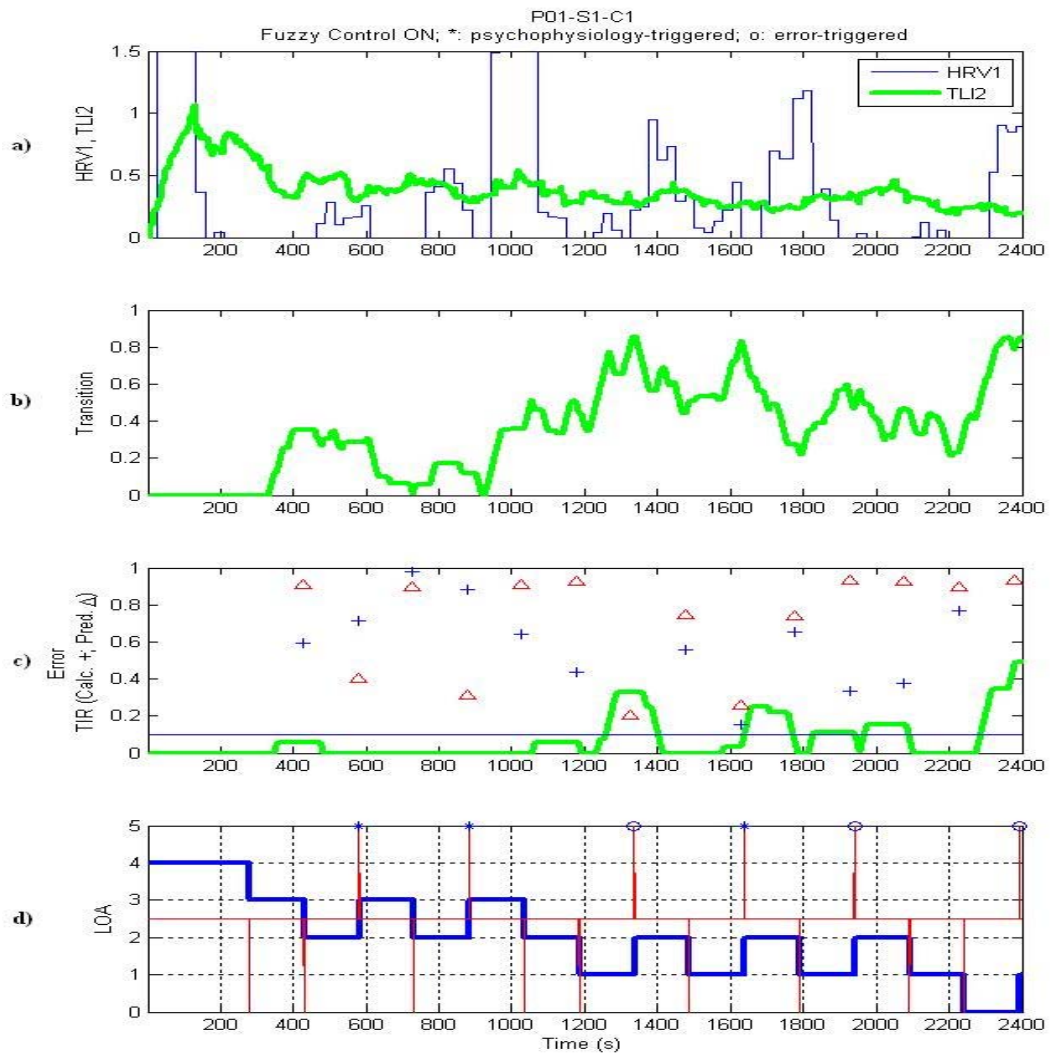


Fig.8. Output results during the third period of time of 40 minutes 'Condition 1 of the 'Session 1' based model for 'Participant 01'.

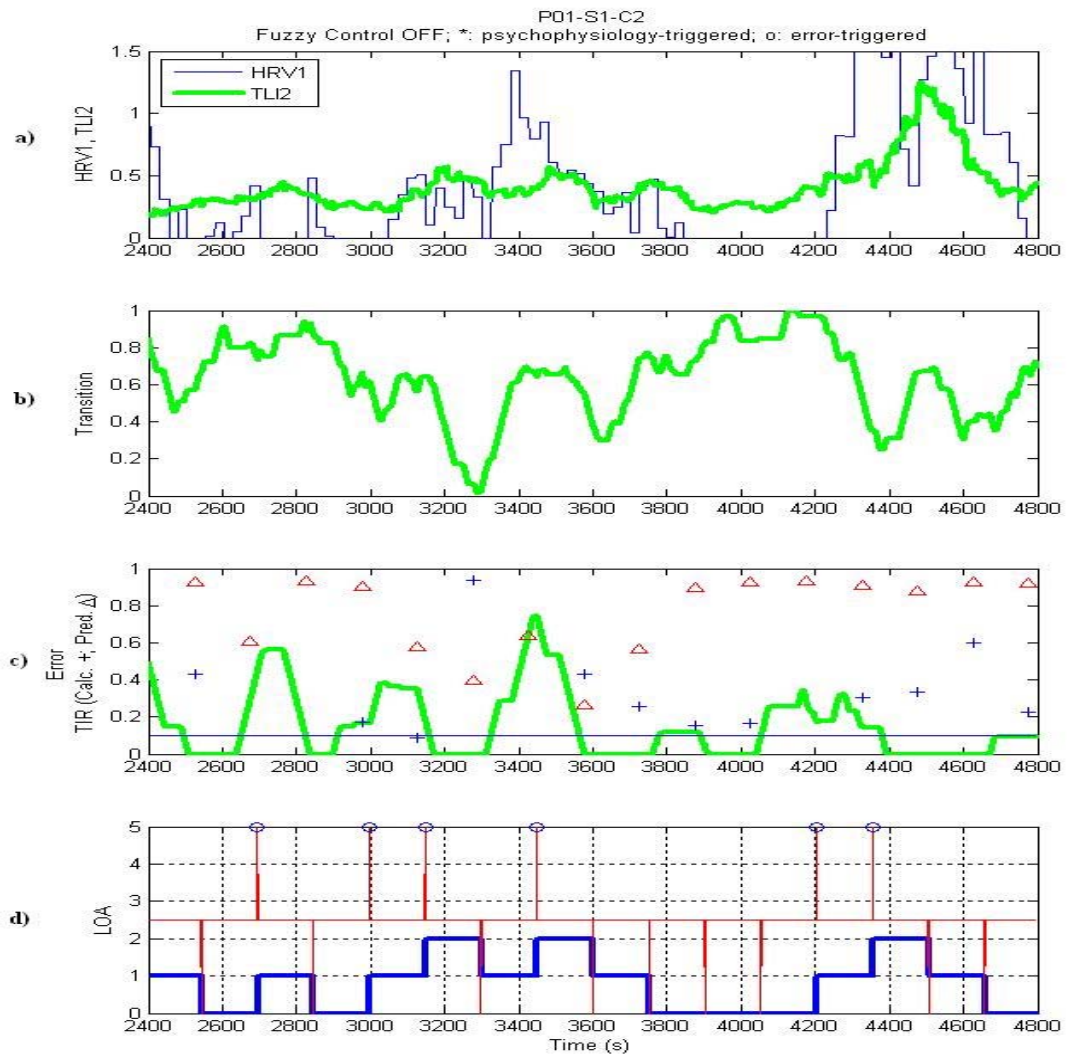


Fig.9. Output results during the third period of time of 40 minutes 'Condition 2' of the 'Session 1' based model for 'Participant 01'.

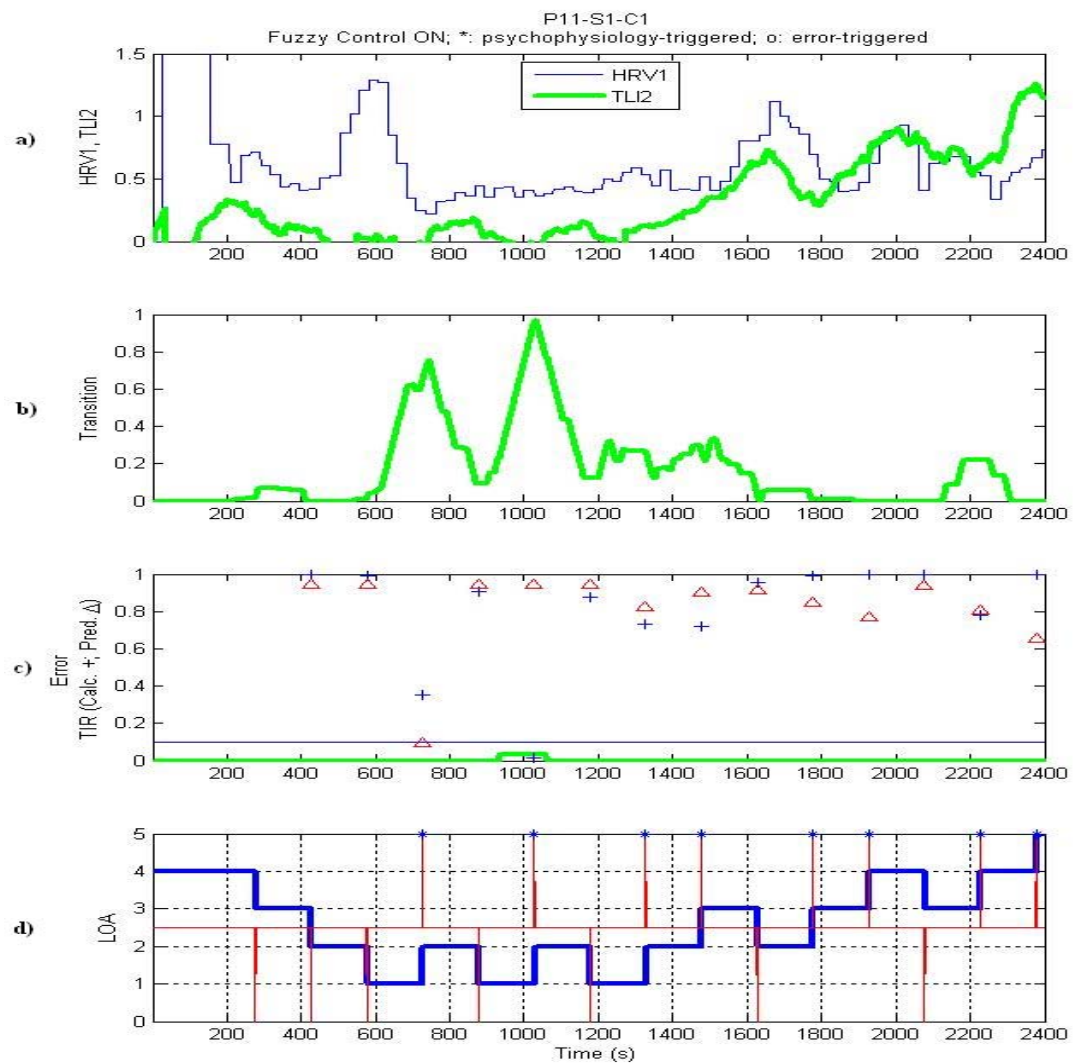


Fig.10. Output results during the third period of time of 40 minutes 'Condition 1 of the 'Session 1' based model for 'Participant 11'.

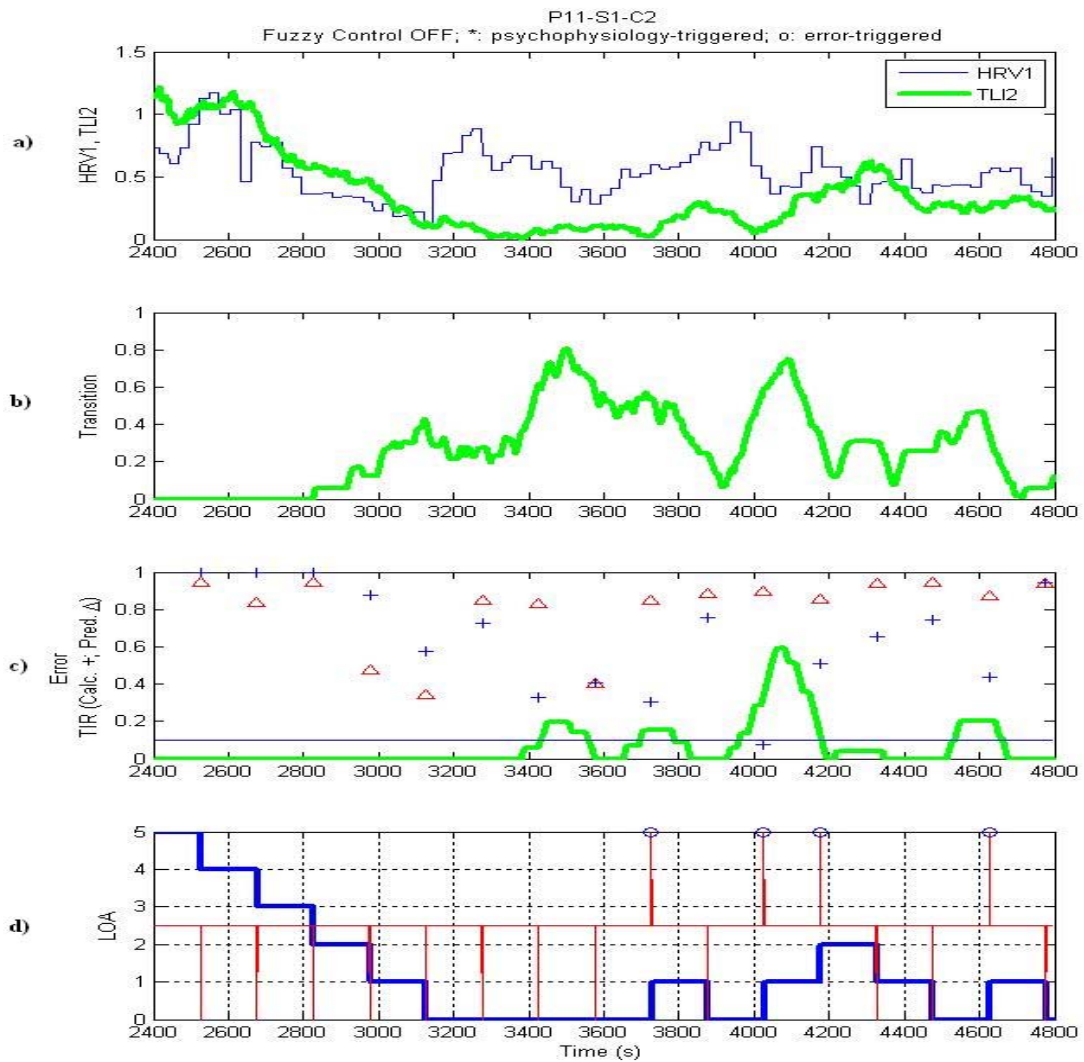


Fig.11. Output results during the third period of time of 40 minutes 'Condition 2 of the 'Session 1' based model for 'Participant 11'.

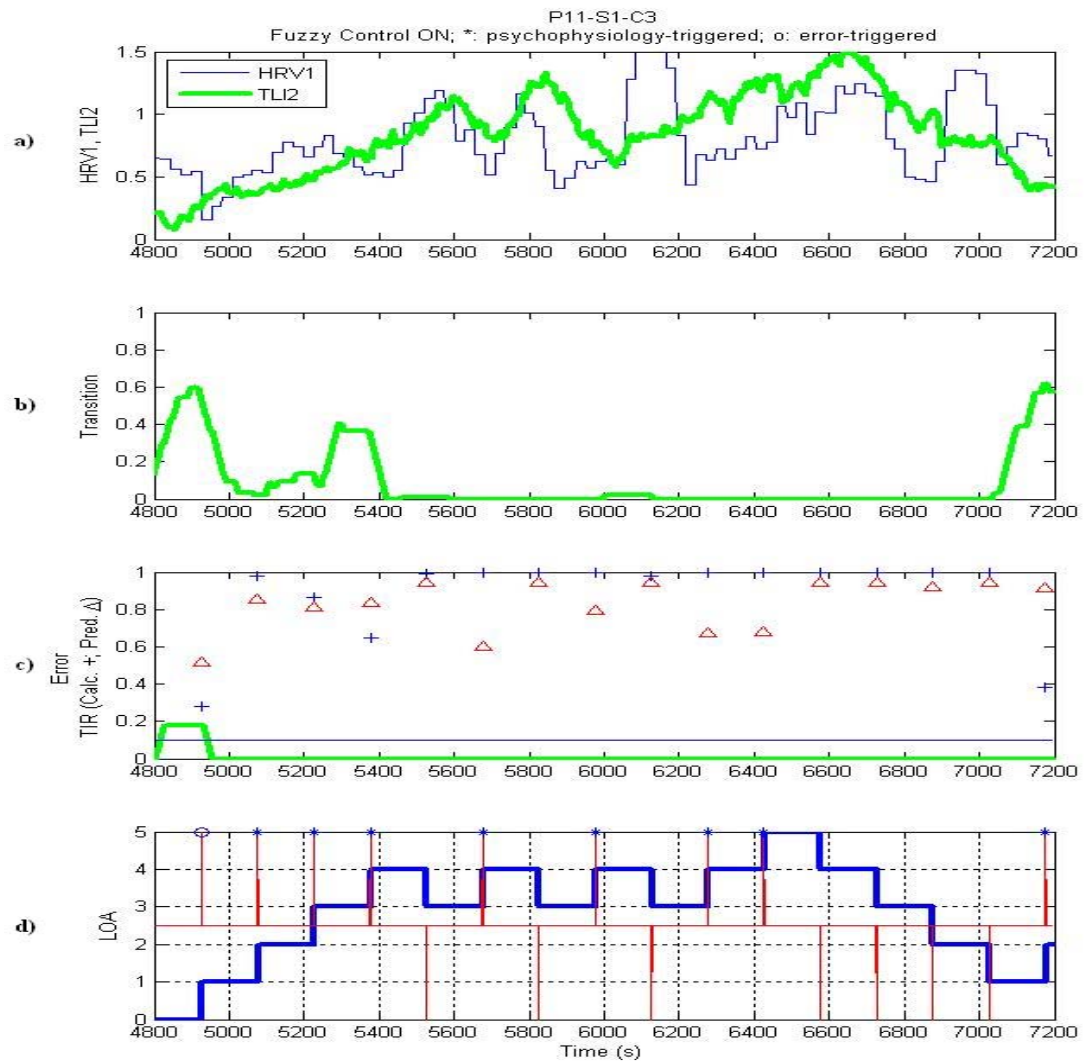


Fig.12. Output results during the third period of time of 40 minutes 'Condition 3' of the 'Session 1' based model for 'Participant 11'.

TABLE I
FUZZY RULE BASE FOR THE TIME-IN-RANGE PREDICTOR. MODEL OUTPUT: TIME-
IN-RANGE.

TLI2	HRV1				
		S	M	B	VB
	S		H	VH	VH
	M	M	H	H	VH
	B	L	M	H	N
	VB	L	L		

TABLE II
FUZZY RULE BASE FOR THE SYSTEM-IN-ERROR PREDICTOR. MODEL OUTPUT: SYSTEM-IN-ERROR.

TIR	SIT			
		L	M	H
	L	L	M	H
	M	L	L	H
	H	L	L	H

TABLE III
INDIVIDUAL STATISTICAL RESULTS FROM REAL-TIME TRIALS -'CONDITION 1'; SP: SYSTEM
PERFORMANCE, FP: FUZZY PREDICTOR.

Subject Code	LOA (Mean)	LOA (SD)	LOA shifts (SP)	LOA shifts (FP)	SIE (Mean)
P01	2.040	1.076	3.000	3.000	0.068
P02	1.665	1.244	5.000	1.000	0.156
P05	1.788	1.169	1.000	5.000	0.018
P06	2.920	1.253	0.000	6.000	0.004
P08	1.473	1.351	3.000	2.000	0.059
P09	0.967	1.388	1.000	1.000	0.008
P10	1.470	1.354	1.000	3.000	0.017
P11	2.573	1.077	0.000	8.000	0.002
P12	1.533	1.306	4.000	1.000	0.098
Average	1.825	1.247	2.000	3.333	0.048

TABLE IV
INDIVIDUAL STATISTICAL RESULTS FROM REAL-TIME TRIALS-'CONDITION 2'; SP: SYSTEM
PERFORMANCE, FP: FUZZY PREDICTOR.

Subject Code	LOA (Mean)	LOA (SD)	LOA shifts (SP)	LOA shifts (FP)	SIE (Mean)
P01	0.815	0.727	6.000	0.000	0.153
P02	0.309	0.578	2.000	0.000	0.065
P05	0.993	0.865	8.000	0.000	0.134
P06	0.123	0.328	1.000	0.000	0.017
P08	0.371	0.599	3.000	0.000	0.071
P09	0.000	0.000	0.000	0.000	0.004
P10	0.063	0.243	1.000	0.000	0.012
P11	1.265	1.449	4.000	0.000	0.066
P12	0.688	0.919	5.000	0.000	0.139
Average	0.514	0.634	3.333	0.000	0.073

TABLE V
INDIVIDUAL STATISTICAL RESULTS FROM REAL-TIME TRIALS-'CONDITION 3'; SP: SYSTEM
PERFORMANCE, FP: FUZZY PREDICTOR.

Subject Code	LOA (Mean)	LOA (SD)	LOA shifts (SP)	LOA shifts (FP)	SIE (Mean)
P01	2.412	0.912	4.000	3.000	0.092
P02	0.981	0.865	2.000	7.000	0.037
P05	1.248	0.831	2.000	6.000	0.090
P06	1.973	1.234	2.000	7.000	0.027
P08	0.623	0.698	6.000	0.000	0.083
P09	0.315	0.585	2.000	1.000	0.020
P10	0.109	0.378	2.000	0.000	0.056
P11	2.893	1.291	1.000	8.000	0.010
P12	1.052	1.028	6.000	2.000	0.160
Average	1.289	0.869	3.000	3.778	0.064

TABLE VI
OVERALL ANALYSIS OF REAL-TIME TRIALS PERFORMANCE - 'SESSION 1'

Cond.	LOA (Mean)	LOA (SD)	LOA shifts (SP)	LOA shifts (FP)	SIE (Mean)
1	1.825	1.247	2.000	3.333	0.048
2	0.514	0.634	3.333	0.000	0.073
3	1.289	0.869	3.000	3.778	0.064

TABLE VII
OVERALL ANALYSIS OF REAL-TIME TRIALS PERFORMANCE - 'SESSION 2'

Cond.	LOA (Mean)	LOA (SD)	LOA shifts (SP)	LOA shifts (FP)	SIE (Mean)
1	1.223	1.269	2.429	1.143	0.042
2	0.488	0.506	4.167	0.000	0.076
3	1.229	0.881	3.667	2.167	0.056

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