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Cognitive pilot-aircraft interface for single-pilot operations

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ABSTRACT

Considering the foreseen expansion of the air transportation system within the next two decades and the opportunities offered by higher levels of automation, Single-Pilot Operations (SPO) are regarded as viable alternatives to conventional two-pilot operations for commercial transport aircraft. In comparison with current operations, SPO require higher cognitive efforts, which potentially result in increased human error rates. This article proposes a novel Cognitive Pilot-Aircraft Interface (CPAI) concept, which introduces adaptive knowledge-based system functionalities to assist single pilots in the accomplishment of mission-essential and safety-critical tasks in modern commercial transport aircraft. The proposed CPAI system implementation is based on real-time detection of the pilot's physiological and cognitive states, allowing the avoidance of pilot errors and supporting enhanced synergies between the human and the avionics systems. These synergies yield significant improvements in the overall performance and safety levels. A CPAI working process consisting of sensing, estimation and reconfiguration steps is developed to support the assessment of physiological and external conditions, a dynamic allocation of tasks and adaptive alerting. Suitable mathematical models are introduced to estimate the mental demand associated to each piloting task and to assess the pilot cognitive states. Suitably implemented decision logics allow a continuous and optimal adjustment of the automation levels as a function of the estimated cognitive states. Representative numerical simulation test cases provide a preliminary validation of the CPAI concept. In particular, the continuous adaptation of the flight deck's automation successfully maintains the pilot's task load within an optimal range, mitigating the onset of hazardous fatigue levels. It is anticipated that by including suitably designed Psychophysiological-Based Integrity Augmentation (PBIA) functionalities the CPAI system will allow to fulfil the evolving aircraft certification requirements and hence support the implementation of SPO in commercial transport aircraft.

1. Introduction

Due to the substantial growth in commercial air travel demand and the aggravating global shortage of qualified pilots [29], Single-Pilot Operations (SPO) are likely to be extended beyond military and general aviation operations in the next two decades [12,15]. Single-pilot airline transport aircraft are nonetheless associated with substantial challenges, as the individual pilot on board may suffer incapacitation, potentially resulting in fatal accidents. Additionally, compared to conventional two-pilot operations, SPO pose greater cognitive demands on the individual pilot. These demands, should they exceed the pilot's cognitive capacity, will adversely affect the pilot's ability to accomplish the task-at-hand. [20]. Pilots whose capabilities fall short of task requirements can make errors in safety-critical duties, leading to fatal accidents. Consequently, the transition to SPO require substantial increases in automation support both in the flight deck and on the ground as well as significant changes in the roles and responsibilities of pilots and Air Traffic Management (ATM) operators. In particular, the primary duties of pilots are progressively shifting towards supervisory roles, intervening only when necessary [33]. These new roles require a corresponding evolution in the Human-Machine Interfaces and Interactions (HMI^2). Current HMI^2 are static and do not take into consideration the dynamic variations in cognitive task loads [50]. Additionally, as part of the Technology Horizons project, the United States (US) Air Force identified that natural human capacities and advanced technologies become increasingly mismatched and humans will be the weakest component in the generalised processes and systems by 2030 (US [52]). Therefore, a dynamic sharing of tasks between human pilots and avionics systems through advanced HMI^2 will be required to achieve better overall performance.

Research in the past decade has examined the use of intelligent HMI^2 systems in dynamically reconfiguring cockpit displays according to the operator's task and actions [39], as well as reacting to external events [28]. Terveen [51] discusses three key issues

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concerning adaptive systems: how information is acquired, how the system represents and reasons the received information and how information is used. In the Taxonomy of Adaptations, Feigh et al. [21] describes four ways in which information can be used: modifying the task allocation between human and machine, the task scheduling based on priority, the machine's interaction with the user as well as the formats and functions. Developments in wearable and contactless sensing technologies have enabled new ways of acquisition, interpretation and exploitation of human physiological data in HMI^2, as in the case of activity recognition [38]. In our research, a Cognitive Pilot-Aircraft Interface (CPAI) is proposed to implement these new sensing technologies in an expert avionics decision support system. This novel system can dynamically assess the pilot's cognitive capacity through sensors that track his/her physiological measurables and complement it through system adaptation. In particular, CPAI modifies the task allocation between pilots and systems, generates suitable alerts and modifies the information presented to the pilot with adaptive interfaces. Thanks to these functionalities currently unavailable in the flight decks of commercial transport aircraft, CPAI can prevent human errors in the cognitive domain and optimise the interaction and task allocation between the human and aircraft systems. Consequently, commercial transport aircraft equipped with CPAI will potentially fulfil evolving certification standards for SPO.

This paper presents the conceptual design, development and numerical verification activities of CPAI. Model verification activities are performed by means of representative simulation case studies to preliminarily validate the technical feasibility of CPAI. Six layers of variables including operational conditions, environmental conditions, physiological measurables, cognitive indicators, system and interface variables are identified for the mathematical model development. The mental workload is determined by means of two distinct methods. Physiological data including heart, respiratory and blink rates are used to infer the current cognitive states using suitably defined empirical models. Furthermore, environmental and operational conditions are analysed to generate future mental workload demand estimates.

The CPAI presented in this paper is an expert decision support system, which exploits the input information on monitored and predicted cognitive states to enhance operational safety and efficiency. In particular, system adaptation, driven by expert decision logics, is implemented based on the key variables and mathematical relationships. The opportunity of dynamically adapting the decision logics based on the characteristics of the monitored individual and on the particular flight phase is highlighted and further developments in this direction are outlined.

1.1. Single pilot operations

Current commercial transport aircraft adopt two-pilot flight crews, comprising of a Pilot Flying (PF) and a Pilot Non-Flying (PNF). Both of them are on board and the primary responsibility shared between them consists in controlling the aircraft while it is flying or moving on the ground. Four fundamental duties are shared between the PF and the PNF: *aviate, navigate, communicate, manage*. SPO are defined such as these tasks are conducted by only one pilot in the Flight Deck (FD) (CASR 1998-REG 61.010). Compared to conventional two-pilot operations, the primary duty of the single on board pilot (PF) is still controlling the aircraft. However, ground-based human operators located in the Airline Operations Centre (AOC) are able to support the airborne PF in SPO [32]. AOC operators monitor the aircraft mission and assist the PF in the role of dispatchers. In case of emergency, AOC operators upgrade their roles to ground-based first officers, who assist the on board pilot by real-time voice coordination with the FD and control of the aircraft through the HMI^2 in the ground workstation [13]. Fig. 1 presents a comparison between the interactions involved in two-pilot, single-pilot and Remotely Piloted Aircraft Systems (RPAS) operations, including Air Traffic Controllers (ATCo).

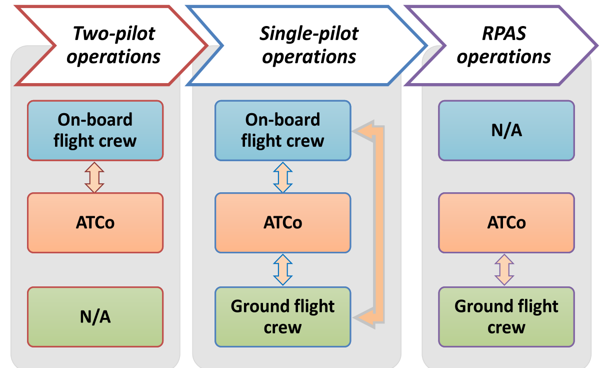


Fig. 1. Human operator interactions in different operational settings.

As mentioned above, the primary responsibilities of PF in SPO include a variety of mission-essential and safety-critical tasks [1,19]:

Aviate

- Monitor aircraft flight, traffic and weather statuses;
- Manually fly the aircraft by controlling stick, pedal and throttle;
- Detect and resolve potential in-flight conflicts and hazards;
- Setup autopilot to assist/supplement in attaining the desired flight profile.

Navigate

- Monitor the aircraft position and course;
- Select and configure applicable navigation modes;
- Configure the cleared flight plan or 2/3/4-dimensional trajectory in the Flight Management System (FMS).

Communicate and coordinate

- Communicate and coordinate with ATCo and AOC operators;
- Dispatch declarations of urgency and emergency.

Manage

- Monitor the status of aircraft systems;
- Monitor compliance with the Required Communication, Navigation and Surveillance Performances (RCP, RNP, RSP);
- Supplement or supersede the system as required.

The primary responsibilities of the AOC operators include [12,32]:

- Monitor SPO aircraft throughout the flight;
- Support the PF in decision making as a co-pilot would;
- Assist the PF in following the Reference Business Trajectory (RBT) en route to maximise the PF's attention on other tasks;
- Share the PF workload in unexpected and challenging conditions (e.g. system failures, adverse weather);
- Assist in the critical approach and landing phases;
- Take over the PF's responsibility in the event of incapacitation;
- Communicate and coordinate with PF and ATCo.

The ATCo also plays a significant role in SPO in adverse conditions such as system failures and severe weather conditions.

2. CPAI conceptual design

In the CPAI design, a human-centred approach is adopted, for which the system adapts to optimise human-machine interactions and overall performance. This design is based on the concept of adaptive automation, which was explored in previous research particularly to cope with complex systems [21,30,35,53]. In particular, automation can be adapted based on the operator's workload, which is inferred from a number of variables, such as external events, measurable physiological variables, or the actions undertaken by the human operator. In our paper, CPAI estimates the operator's cognitive state based on the first two of these. The three fundamental objectives adopted for the design of CPAI are:

- **Design for complementing perception and cognition capabilities of human pilots**

Pilots, as human beings, have perception and cognition limitations [11]. For example, perceptual tunnelling is a phenomenon in which an individual under high stress becomes focused on one stimulus and neglects other important information or tasks [54]. This phenomenon might happen when carrying out monitoring tasks and this might lead to the late detection of issues. Therefore, the CPAI shall augment the cognitive capabilities of the pilot, such as visual and auditory perception, attention and memory.

- **Design for preventing pilot errors**

Human error is a primary factor in air accidents and incidents. Around 70% of air accidents are related to human errors [31] and several negative factors associated with human cognition, such as fatigue and stress, can severely impact pilots' performance, potentially compromising the ability to accomplish their duties thereby representing risks to flight safety. Therefore, CPAI shall take into account potential threats from the cognitive perspective and prevent these impacts by means of appropriate information processing and decision support.

- **Design for achieving optimal pilot-aircraft interaction**

Increases in FD automation are intended to significantly reduce the pilot workload and increase efficiency/safety of operations. However, other problems such as intuitiveness and trustworthiness of automation's behaviour, spikes of mental workload during critical flight phases and the boredom in the cruise phase are known causes of safety threats [34,42]. Consequently, the CPAI shall mitigate these interaction problems and obtain an optimal functional allocation of tasks between pilots and advanced aircraft systems, particularly exploiting automation to perform recurrent low-level actions and the human to perform high-level evaluations and decisions.

2.1. CPAI requirements

In order to achieve these fundamental design objectives, the CPAI system design requirements include:

- CPAI-REQ-001-the CPAI shall monitor human physiological and cognitive states in real time.
- CPAI-REQ-002-the CPAI shall assess operational and environmental conditions in real time.
- CPAI-REQ-003-the CPAI shall provide pilots the most appropriate assistance through adjustment of automation levels.
- CPAI-REQ-004-the CPAI shall minimize the cognitive load of pilots.
- CPAI-REQ-005-the CPAI shall enhance the situational awareness of human operators.
- CPAI-REQ-006-the CPAI shall minimise reliance on human memory for any system operating procedure.
- CPAI-REQ-007-the CPAI shall feature clear and unambiguous display formats and functions of system modes, sub-modes and navigational data.
- CPAI-REQ-008-the CPAI shall provide caution or warning alerts to relevant personnel such as AOC operators in case of pilot impairment or incapacitation.
- CPAI-REQ-009-the CPAI shall support the entire range of activities that human operators need to perform in a 4D Trajectory Based Operations (TBO) context.
- CPAI-REQ-010-the CPAI shall provide the capabilities to create, modify, review and enact 4DT intents.

2.2. Conceptual working process

The CPAI working process is subdivided in three separate stages: sensing, estimation and reconfiguration. First, pilot physiological states and external conditions are collected from a combination of sensors and real-time monitoring systems. Second, cognitive states such as mental workload and fatigue levels of the pilot are estimated based on physiological variables measured by CPAI. Additionally, the mental demand associated with new tasks is estimated automatically based on detected variations in external conditions. Third, the CPAI predicts the cognitive condition of the pilot for the next instant and reconfigures the system and interface to keep them at an optimal cognitive condition to achieve the best performance. Caution and warning flags are generated if the pilots' physiological states are detected in an unacceptable range (e.g. overload or underload conditions). The CPAI conceptual working process is illustrated in Fig. 2.

2.3. CPAI functionalities

In order to achieve safer, more effective and efficient operations, an optimal interaction between the human and the systems is necessary. In our research, four intelligent and adaptive functions including real-time physiological monitoring, continuously environmental and operational monitoring, adaptive alerting and dynamic task allocation are designed to attain balanced cooperation between pilots and advanced aircraft systems.

2.3.1. Real-time physiological assessment

Recent publications in the area of aerospace engineering and aviation have studied the monitoring and augmentation of the operator's cognitive workload through real-time tracking of physiological measurables. These include systems that monitor the user's cognitive state through the use of gaze tracking [7,10,40] and neurophysiological signals ([3,25]). Such systems are also being researched in the areas of driving [9,26] and in personal health applications [37]. In the case of CPAI, a continual assessment of the human cognitive state is made by monitoring physiological measurables. These include neural, (e.g. Event-Related brain Potential - ERP [5]), cardiovascular (e.g. heart rate, heart rate variability [27] and sensory systems (e.g. blink rate, eye movements and pupil diameter). For example, blink is considered one of the most effective measures of mental workload (MWL) and it has been proven to decrease with the growth of MWL [14]. Electroencephalography (EEG), as a physiological measure of the momentary functional state of cerebral structures, provides information on inattention and high cognitive workload. The real-time monitoring will be carried out adopting a combination of on-body and off-body sensory equipment, including the smart vest [41] and/or non-wearable health devices such as eye tracking systems as part of the CPAI system. The types of devices that can be used for monitoring

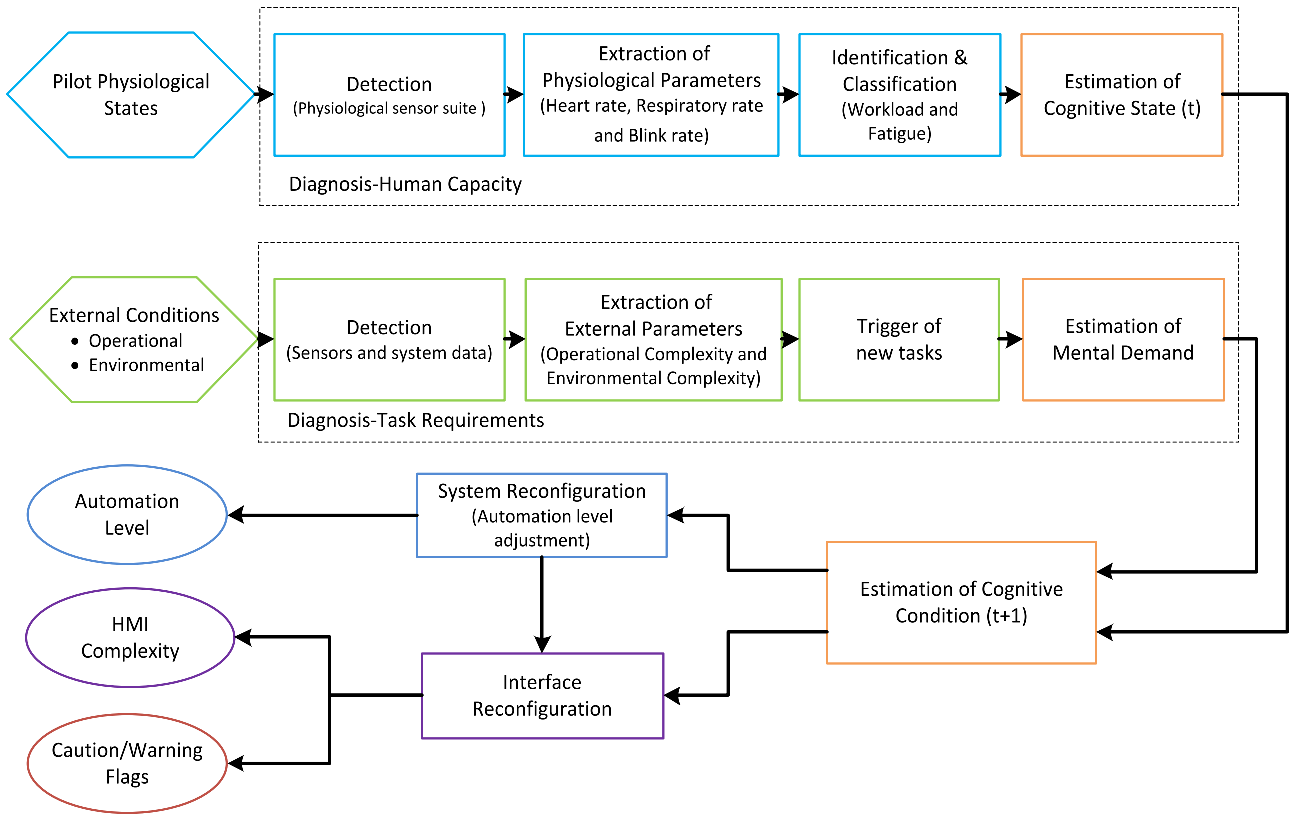


Fig. 2. Conceptual working process of CPAI.

Table 1
Physiological monitoring suite for SPO.

Monitoring equipment	Variables
Smart shirt [6]	Photoplethysmogram (PPG) Electrocardiogram (ECG) Blood pressure Heart rate Body temperature Galvanic skin response (GSR)
Cockpit camera – ground monitoring	Facial expression Pilot behaviour
Eye-tracking –wearable or remote [17]	Blink rate Blink interval Blink duration Pupil diameter Saccadic behaviour
Neural activity – fNIRS, EEG [5,49]	Brain hemodynamic response - changes in blood oxygenation Brain activity Mental workload

the physiological measurables in SPO are summarised in Table 1. Other technologies such as posture tracking, functional Near Infrared Spectroscopy (fNIRS) and pupillometry are also being investigated [4,46]. Eye tracking data and observations on the pilot behaviour and facial expression are particularly important to develop the specific knowledge base of CPAI for each individual pilot.

2.3.2. External conditions assessment

The external conditions consist of environmental (e.g. weather, orographic and topographic complexities) and operational conditions including different flight phases, ATM and airlines constraints, as well as several parameters such as velocity, position and attitude. All of them affect the human performance significantly and hence the CPAI shall consider these parameters when it conducts a task reallocation. For example, automation would be adjusted to a relatively high level during take-off, approach and landing phases while to a low level in the cruise to maintain the pilot's mental workload at a particular threshold, avoiding overload or losses of situational awareness. CPAI obtains detailed information regarding the operational and environmental conditions from the Avionics Data Networks (ADN). ADN data include information regarding the type, characteristics and criticality of future operational tasks.

2.3.3. Dynamic task allocation

Based on the continuous assessment of human cognitive states and the estimated task mental demand associated with environmental and operational conditions, the CPAI can prompt a task reallocation between the automation systems and human operators. For example, if a spike in mental workload of the pilot is predicted, the CPAI can pre-sort and pre-process information shown on the avionics displays and determine optimal actions, as well as increase the level of automation of on-board systems to support him/her. On the other hand, if the pilot is predicted to lose situational awareness due to high levels of automation support, CPAI can adjust automation to lower levels in order to keep the pilot mentally engaged.

2.3.4. Adaptive alerting

Traditional alerting in the Flight Director (FD) involves visual, auditory cues or a combination thereof. Usually, the forms of alerting are fixed. However, they might be ineffective in particular conditions due to human limitations, as in the case of perceptual tunnelling, a phenomenon in which an individual under high stress becomes focused on one stimulus and neglects to attend to other important information or tasks. Typically, people cannot avoid or solve this and similar problems by themselves. Therefore, adaptive alerting can be designed to prevent such occurrences. Haptic cues can be integrated with sticks or seats as a new form of alerting in the FD. Furthermore, visual, auditory and haptic alert forms can be used separately or in combination depending on the situation and considering input data from equipped sensors.

2.3.5. Detection and notification of abnormal pilot conditions

Since the on-board pilot is the only human operator in the FD, his/her physiological and psychological conditions are safety-critical. An early detection of abnormal physiological or psychological conditions can interrupt the sequence of events that lead to catastrophic failures and should therefore be implemented as part of the CPAI design. Thanks to the real-time physiological assessment functionality, CPAI can promptly detect the occurrence of abnormal conditions including overload, impairment and incapacitation affecting the pilot. Adopting an integrity augmentation approach [44,45], predictive and reactive annunciations consisting of timely and usable alerts can be generated by CPAI, allowing AOC operators and ATCo to implement corrective actions. For this purpose, upon detection of abnormal conditions, CPAI automatically generates opportune various alert flags to notify human operators, including: cognitive advisory flag, cognitive warning flag and cognitive incapacitation flag. In the Communication, Navigation, Surveillance, ATM (CNS/ATM) and Avionics (CNS+A) context, these flags can be dispatched via the Next Generation Aeronautical Data Links (NG-ADL). Data exchanged between Next Generation Flight Management Systems (NG-FMS) and 4-Dimensional Trajectory Planning, Negotiation and Validation (4-PNV) systems enable ATCo and AOC operators to be alerted and as a result, corrective measures can be implemented [23,43]. For these purposes, the CPAI integrates a Psychophysiological-Based Integrity Augmentation (PBIA) functionality to generate alert flags and dispatch them to both on-board pilot and/or ground-based human operators in case of pilot cognition impairment or incapacitation.

2.4. CPAI architecture

The detailed CPAI architecture is shown in Fig. 3. The developed CPAI architecture is primarily based on the core functionalities, and specifically: physiological state assessment and external condition assessment and dynamic task allocation. This set of functionalities employs suitable models of the human operators' cognitions and intentions, and of the situation. To accomplish the aforementioned functionalities in line with the CPAI working process, the three CPAI modules are:

Sensing module – It retrieves the raw data detected by various sensors (e.g. physiological sensors) and collects the parameters related to external conditions including the environmental and operational conditions. The retrieved and selected data are passed as input to CPAI estimation models.

Estimation module – It estimates in real-time the cognitive state (i.e. fatigue, stress, attention and workload levels, etc.) of the pilot and mental demand estimation associated with planned tasks. The estimation module performs a weighted sum of these two values to predict the human cognitive condition at the next moment.

Reconfiguration module – This module includes suitable decision logics to determine output states. The input is from the cognitive prediction model and the results drive reconfigurations of avionics systems. Three adaptive sub-modules are included in the reconfiguration module. An adaptive automation module manages task distribution between the automation systems and pilots via a Level of Automation (LOA) switcher and a task manager. An adaptive interface module supplies optimal amounts of information through selected display formats to pilots according to a Graphical User Interface (GUI) page manager and a format manager. Additionally, an adaptive alerting module provides changeable forms of caution and warning flags to pilots.

2.5. Overview of CPAI in the Next Generation Flight Management System (FMS)

During flight, the flight deck enables pilots to carry out their tasks of aviating, navigating, communicating and managing the aircraft. The pilot interacts with the avionics systems through cockpit interfaces, a few of which are highlighted in Fig. 4. These include the Navigational Display (ND), the Multipurpose Control Display Unit (MCDU), the Engine-Indicating and Crew-Alerting System (EICAS) and the Primary Flight Display (PFD) depicted left-to-right in Fig. 4. In particular, the MCDU is an interface for the pilot to control the Flight Management System (FMS). The FMS is primarily responsible for providing automated navigation and guidance services from take-off to landing. The software component embedded in the processor performs the following functions:

- Positioning and navigation algorithms including multi-sensor data fusion techniques.
- Trajectory generation and optimisation algorithms.
- Short-term and long-term performance computation algorithms.
- Guidance computations in terms of lateral and vertical guidance algorithms.
- Dual and single flight management mode protocols (for two pilot cockpits).
- Processing, sorting and selection of data bases.
- Built-In-Test Equipment (BITE) and monitoring.
- Interface management.

The FMS augments the pilot's workload by automating certain *inner-loop* tasks. These include computing navigation data, managing flight control systems and engines as well as providing autopilot capabilities. The traditional databases associated with FMS are magnetic deviation, performance and navigation. In addition to these databanks, weather, demographic distribution, digital terrain elevation, environmental and pilot modifiable databases are introduced specifically for time- and performance-based operations.

The NG-FMS provides increased inner-loop automation, creating a greater shift in the pilot's responsibilities from low-level, tactical tasks like aviating and navigating, towards higher-level, strategic tasks like managing and decision-making. However, the pilot is still responsible for directing the aircraft during all phases of flight. In particular, perhaps the most important technological advancement required to support fully autonomous flight (FMS for single pilot operations during pilot incapacitation and for unmanned aircraft) is proving safety in the presence of anomalies such as unexpected traffic, on board failures and conflicting data. Current aircraft automation is mostly considered rigid in the sense that designers have favoured simplicity over adaptability in their strategies. While this has advantages in the certification process, such systems have severe limitations when responding autonomously to scenarios that they are not designed for Atkins [57].

CPAI is introduced within the NG-FMS, providing it with the capability of adaptive automation and thus enhancing the system's adaptability to unanticipated events. CPAI allows the NG-FMS to estimate the pilot's cognitive state through a combination of physiological sensors as well as external complexity inputs from the NG-FMS subsystems. Through beyond-line-of-sight communication datalinks, CPAI provides periodic updates to the ground-based flight crew. During transitions between strategic and tactical tasks, CPAI is able to monitor and aid the pilot, if necessary, in

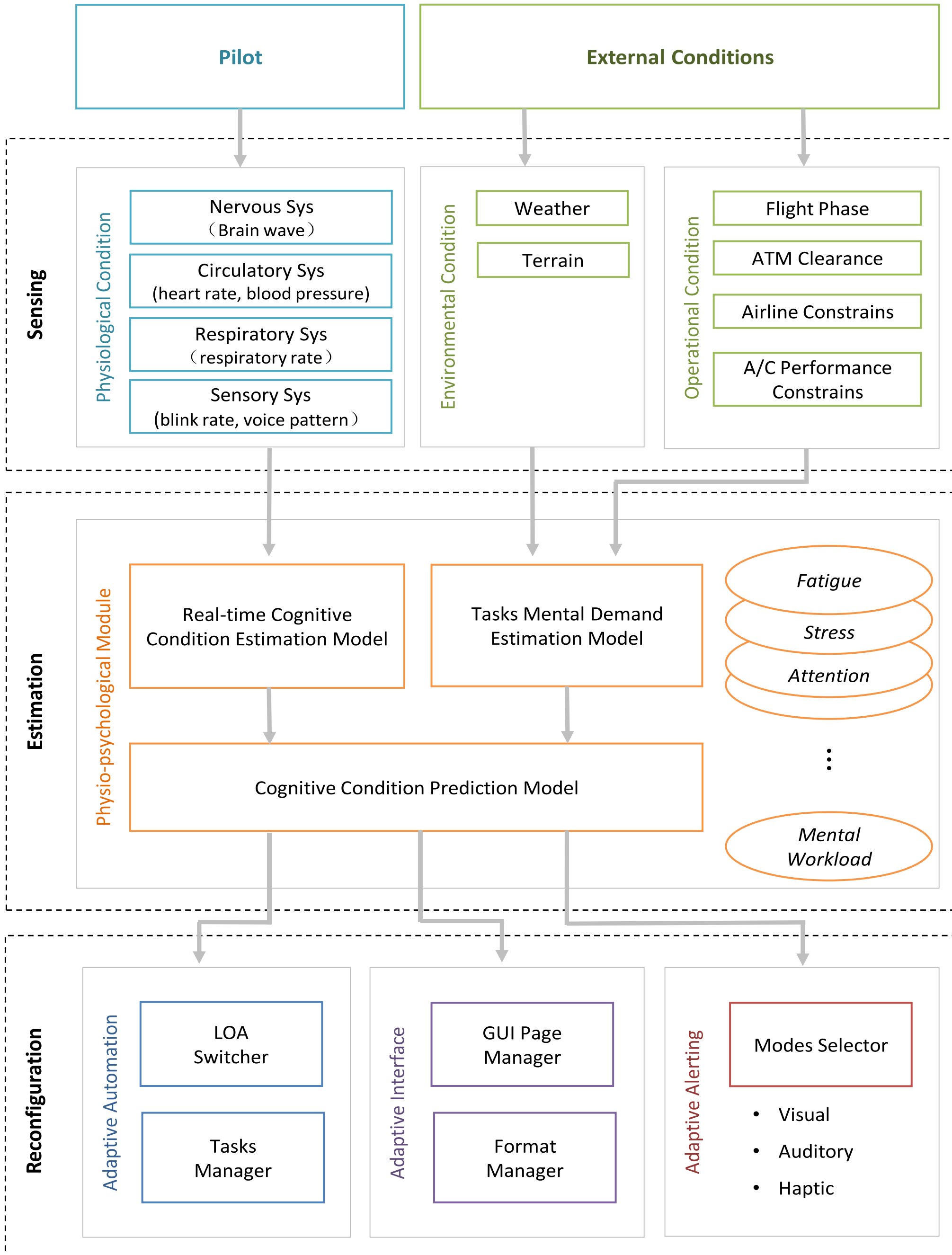


Fig. 3. Detailed CPAI architecture.

making the transition. For example, in the event of pilot overload or incapacitation, the CPAI reduces the pilot's workload by either assuming responsibility of some of these functionalities, or by allocating them to a ground-based flight crew.

3. Mathematical framework

This section presents the mathematical models describing the relationships between detected physiological measurables, external parameters, cognitive indicators and human performance. The CPAI working process involves a number of variables belonging to different layers, which are clearly identified beforehand, in view of the mathematical model development. In particular, based on the literature and on our CPAI conceptual design, six layers of variables are involved in the CPAI working process, including: physiological measurables, operational parameters, environmental parameters, cognitive indicators, system and interface variables. The most representative members of these six layers are listed in Table 2 while relationships between each group of variables are outlined in Fig. 5. The limited number of layers and variables involved supports the adoption of machine learning processes to dynamically assess and adjust the relationship between the various variables.

3.1. Cognitive states estimation

Cognitive indicators can be generally classified into three categories: positive (e.g. vigilance), negative (e.g. fatigue) and interval (e.g. arousal, workload and stress). Positive indicators are directly correlated with increases in human performance while the negative indicators are inversely correlated to performance metrics. In

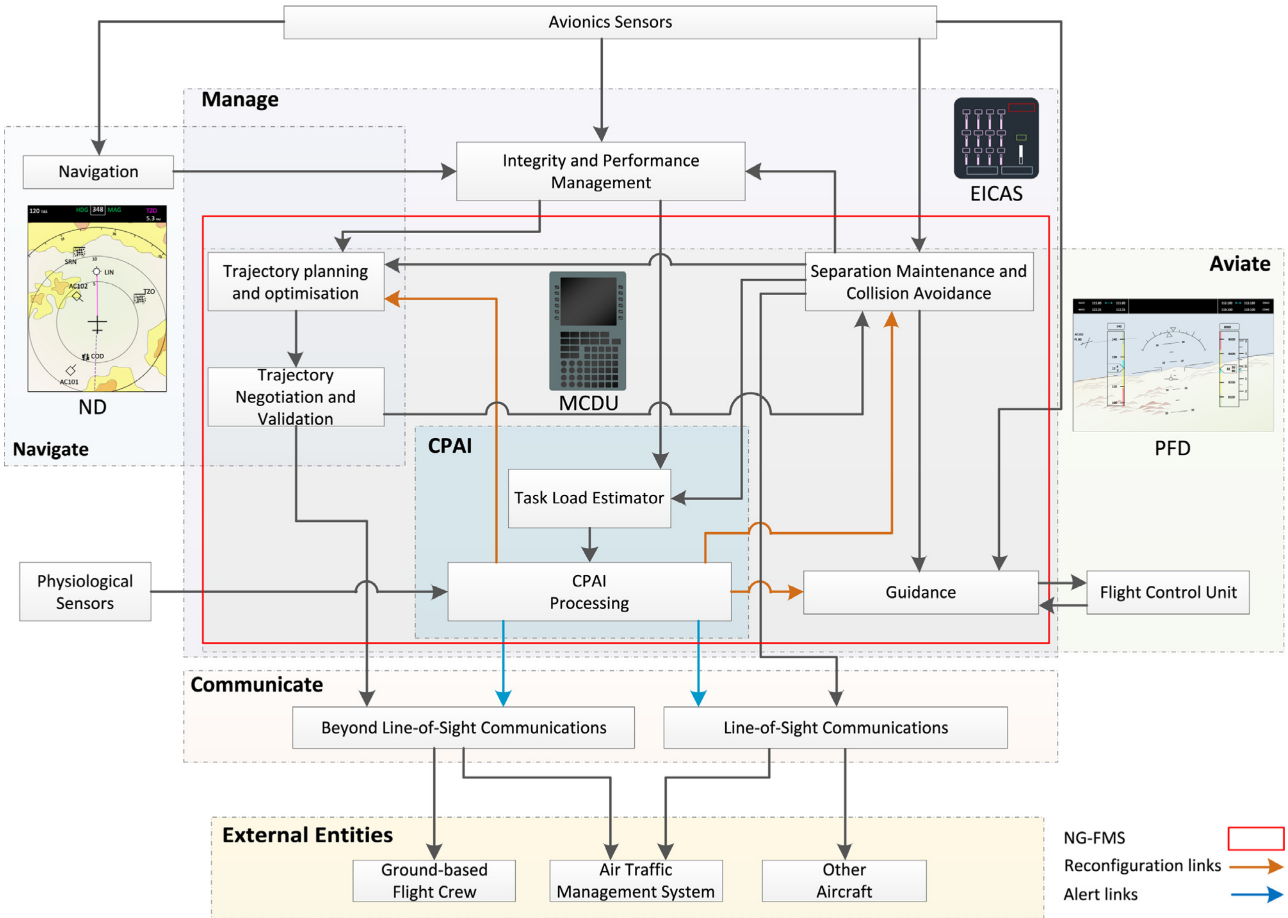


Fig. 4. Integration of CPAI in the NG-FMS.

Table 2
Classification of variables.

Layer	Name	Symbol	Variables
1	Operational conditions	$\gamma_{\mathbf{w}}\ \mathbf{w} \in [1,\ \mathbf{p}]$	Aviate/navigate/communicate/manage tasks, air traffic complexity, aircraft system status, flight phase, mission specificities, ATM directives, airline and aircraft constraints
2	Environmental conditions	$\eta_{\mathbf{v}}\ \mathbf{v} \in [1,\ \mathbf{q}]$	**Weather:** visibility, cloudiness, precipitation **Terrain:** topographical complexity, topological complexity
3	Physiological measurables	$\varphi_{\mathbf{i}}\ \mathbf{i} \in [1,\ \mathbf{m}]$	**Nervous system:** brain waves, fNIRS **Circulatory system:** heart rate, heart rate variability, blood pressure, body temperature **Respiratory system:** respiration rate **Sensory system:** blink rate, blink duration, blink interval, pupil diameter, voice patterns, galvanic skin response, skin temperature **Muscular system:** muscular activity
4	Cognitive indicators	$\psi_{\mathbf{j}}\ \mathbf{j} \in [1,\ \mathbf{n}]$	Vigilance, arousal, mental workload, stress, mental fatigue
5	Performance parameters	$\theta_{\mathbf{k}}\ \mathbf{k} \in [1,\ \mathbf{a}]$	**Accuracy:** error rate / correct percent **Time:** reaction time, time to complete
6	System and interface variables	$\chi_{\mathbf{g}}\ \mathbf{g} \in [1,\ \mathbf{b}]$	**System:** automation level, data processing, decision autonomy, execution autonomy **Interface:** information amount, display formats, caution/warning flags

terms of interval type indicators, the optimum human performance is attained at an intermediate range. As there are no standardised metrics for cognitive indicators, suitable dimensionless cognitive indicator coefficients ψ_j defined in the range between 0 and 1 are introduced to quantitatively represent the level of cognitive states. As shown in Fig. 5, they are determined by CPAI based on the weighted sum of two estimates: cognitive states inferred from real-time physiological measurements ψ'_j and estimates based on external conditions ψ''_j, so that:

$$\psi_j = \delta_m \psi'_j + \delta_e \psi''_j \tag{1}$$

where δ_m is the weight given to estimates based on physiological measurements and δ_e is the weight given to estimates based on external conditions.

3.1.1. Real-time estimation based on physiological measurements

The current jth cognitive state of the pilot at time t, $\psi_{j,t}'$, is inferred by CPAI based on one or more physiological measurables detected at the same instant, $\varphi_{i,t}$. Several cognitive states are involved and each of them corresponds to a set of physiological measurables

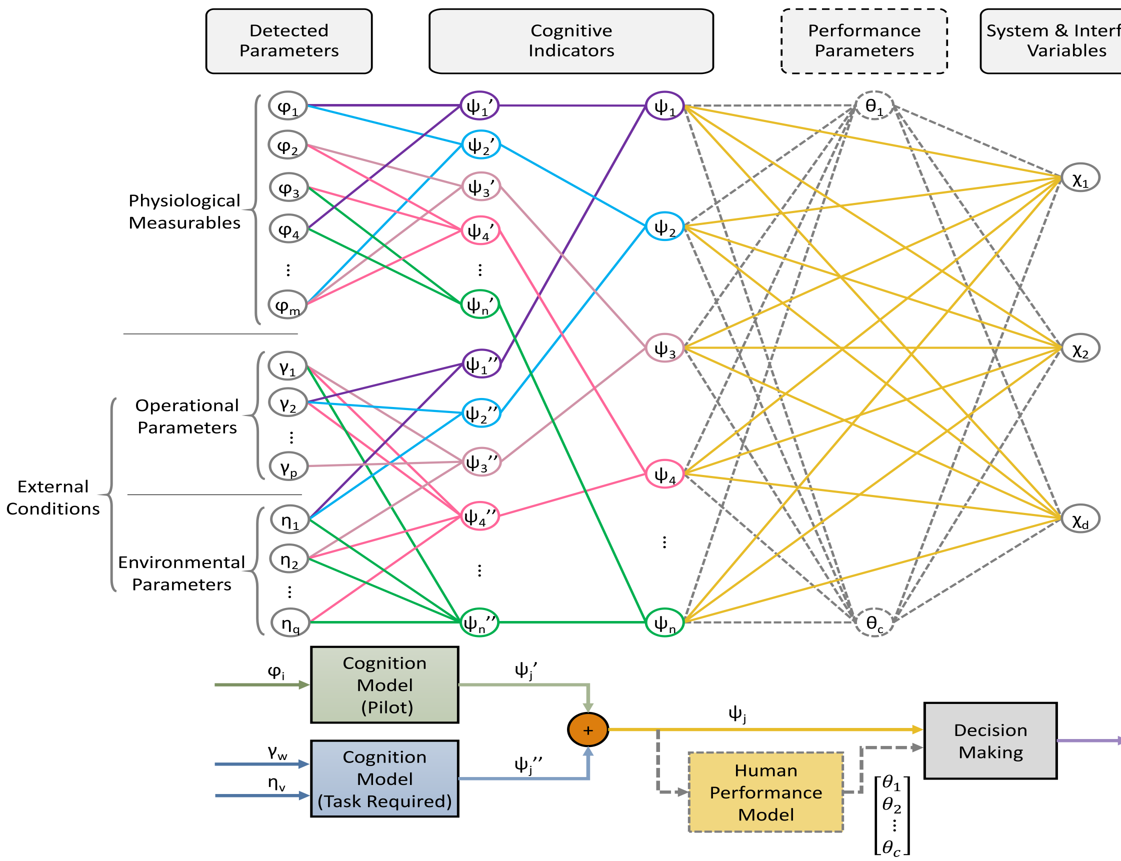


Fig. 5. Outline of variables belonging to different layers and their interactions.

of the pilot, which is described as:

$$\psi'_{j,t} = f(\varphi_{i,t}) \tag{2}$$

As human physiological measurables are typically dependent on the age and gender, reference cognitive states ($\psi_{j,ref}'$) are induced as a baseline. Each reference cognitive state is described as:

$$\psi'_{j,ref} = f\left(\varphi_{i,ref}\right) \tag{3}$$

where the $\varphi_{i,ref}$ is the reference ith physiological measurables detected for the same pilot in healthy rest conditions. Therefore, adopting a linear weighted sum model, the normalised jth real-time pilot cognitive state coefficient ψ_j' is estimated as:

$$\psi'_j = \sum_{i=1}^{n} \alpha_i \cdot \frac{\psi'_{j,t} - \psi'_{j,ref}}{\psi'_{j,ref}} \tag{4}$$

where α_i represent the weights of cognitive indicators while n is the number of cognitive indicators.

The mathematical model for real-time pilot cognitive states is shown in Fig. 6. The inputs of the model include all physiological measurables $\varphi_{i,t}$ while the outputs comprise of all measurable cognitive indicators of pilots.

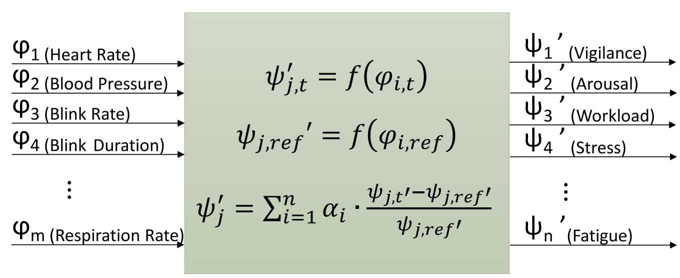


Fig. 6. Mathematical model of real-time pilot cognitive states variation.

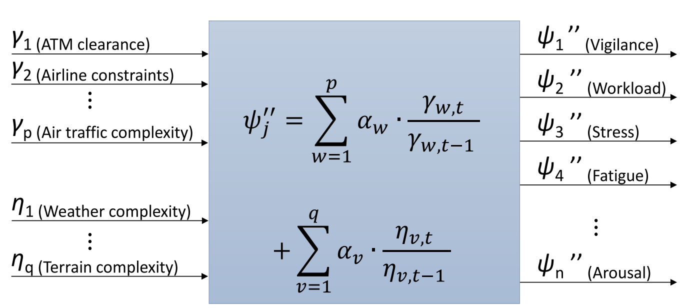


Fig. 7. Mathematical model of human cognition based on detected operational and environmental parameters.

3.1.2. Estimation based on external conditions

Based on the change in external conditions including operational and environmental conditions, new tasks might need to be performed. These tasks may vary in difficulty and in urgency. Consequently, new tasks induce different levels of cognitive load to the pilot and may result in pilot errors if the task mental demand exceeds their capabilities. It is therefore possible to produce estimates of the pilot cognitive states based on external conditions, by adopting a suitable task mental demand model.

In our CPAI system implementation, cognitive states ψ_j” are estimated based on variations in the external conditions. The mathematical model of task mental demand based on variations in detected operational and environmental conditions is shown in Fig. 7. The inputs of the model include all operational and environmental

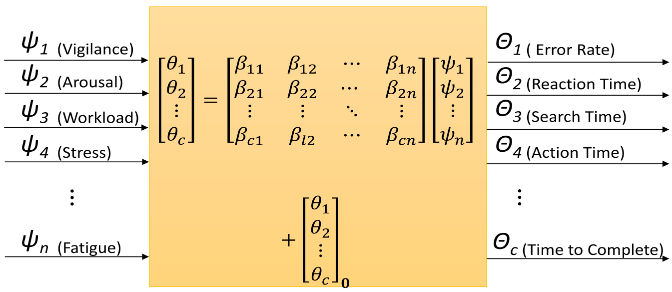


Fig. 8. Mathematical model of human performance.

parameters while the outputs consist of measurable cognitive indicators. The adopted linear weighted sum model is:

$$\psi_j'' = \sum_{w=1}^{p} \alpha_w \cdot \frac{\gamma_{w,t}}{\gamma_{w,t-1}} + \sum_{v=1}^{q} \alpha_v \cdot \frac{\eta_{v,t}}{\eta_{v,t-1}} \tag{5}$$

where α_w represents the weight of γ_w, $\gamma_{w,\,t}$ is the real-time determined operational complexity while the $\gamma_{w,t-1}$ is the operational complexity in the previous epoch; α_v represents the weight of η_v; $\eta_{v,t}$ is the real-time determined environmental complexity while $\eta_{v,t-1}$ is the environmental complexity in the previous epoch.

3.2. Human performance model

Various parameters can be used for assessing the human performance depending on the specific tasks. These parameters can be classified into six categories, including accuracy, time, task battery, domain-specific measures, critical incident measures and team performance measures [24]. As flight safety always plays a dominant role in the aviation domain, the error rate and reaction time are chosen as the primary parameters for assessing the pilot performance. The performance parameters estimated as a function of pilot cognitive states can be described as

$$\begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_c \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1n} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{c1} & \beta_{l2} & \cdots & \beta_{cn} \end{bmatrix} \begin{bmatrix} \psi_1 \\ \psi_2 \\ \vdots \\ \psi_n \end{bmatrix} + \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_c \end{bmatrix}_0 \tag{6}$$

A model of human performance based on this linear relationship is shown in Fig. 8.

4. CPAI implementation

In order to implement the CPAI concept presented in Section 3 and preliminarily validate its technical feasibility, a simulation based on selected subsets of variables (including three physiological measurables, two cognitive indicators, two external condition variables and one system variable) is performed using MATLAB/Simulink. A 35-year-old healthy male pilot is assumed and the simulation consists of a five-hour (18,000 s) flight segment. The presented implementation case study corroborates the conceptual design and the mathematical framework of the CPAI as a whole. The parameters in the mathematical models of the expert system are set based on the literature and pre-defined rules are implemented into the decision logics. The CPAI implementation presented in this case study provides expert decision support and sets the baseline for subsequent developments, including the integration of machine learning techniques and data analytics.

4.1. Model input/output variables

A selection of the various parameters from the literature was performed to define the most relevant ones for this preliminary CPAI implementation.

- Physiological measurables

$\varphi_{\mathbf{HR}}$ **= heart rate:** is a measure of heart activity based on the number of beats per unit time (typically 60 s). The typical heart rate for a healthy woman at rest is 76 bpm (beats per minute) while the resting man has an average heart rate of 70 bpm [2].

$\varphi_{\mathbf{RR}}$ **= respiratory rate:** is a measure of ventilation based on the number of breaths per unit time (typically 60 s). A relaxed healthy adult has a respiratory rate of 12–20 brpm (breaths per minute) [2].

$\varphi_{\mathbf{BR}}$ **= blink rate:** The blink rate is closely related to psychological factors. It increases when the human feels stress or under time pressure. The average blink rate for an adult is 15–20 times per minute (tpm) [2]. Assuming a 35-year-old male commercial pilot, the reference value of heart rate, respiratory rate and blink rate are:

$$\{\varphi_{HR_{ref}} = 73\ \text{bpm},\quad \varphi_{RR_{ref}} = 16\ \text{brpm},\quad \varphi_{BR_{ref}} = 18\ \text{tpm}\}$$

- Cognitive indicators

Mental Workload (MWL) and Mental Fatigue (MFA) are selected for the CPAI application among the many cognitive states as they are recognised as two of the most significant threats to flight safety. MWL and MFA may cause impairment to alertness and performance degradation in pilots.

$\psi_{\mathbf{MWL}}$ **= mental workload coefficient** $(0 \le \psi_{\mathbf{MWL}} \le 1)$**:** represents the level of mental workload. The MWL coefficient should be always kept at the moderate level for attaining the best performance.

$\psi_{\mathbf{MFA}}$ **= mental fatigue coefficient** $(0 \le \psi_{\mathbf{MFA}} \le 1)$**:** represents the level of mental fatigue. The change of mental fatigue is gradual and accumulated. The MFA coefficient should be kept as low as possible to ensure the best performance.

- External condition variables

Changes in external conditions determine the tasks required to be carried out by the pilot, affecting his/her cognitive states. More complex operations and environments may lead to more tasks or more difficult ones. Two external condition variables for the CPAI application are defined below.

$\gamma_{\mathbf{OC}}$ **= operational complexity:** is a measure of the operational situation including flight phase, ATM clearance, airline constraints, aircraft performance constraints and air traffic complexity. The operational complexity is set up on an empirical scale from 1 to 5 correlated with increased mental workload coefficient and mental fatigue coefficient.

$\eta_{\mathbf{EC}}$ **= environmental complexity:** is a measure of the external environment including weather and terrain conditions. Similar to operational complexity, the environmental complexity is set up on an empirical scale from 1 to 5 correlated with increased mental workload coefficient and mental fatigue coefficient.

Table 3
Correlation between operational complexity and TMD.

Operational complexity (η_{OC})	Description	Correlation with TMD
Low	Tasks triggered by low complexity of operational conditions are very few and/or very easy, equating to none or very little load for the pilot.	1/5 in TMD
Moderate	Tasks triggered by moderate complexity of operational conditions are limited in number and/or fairly easy, equating to average load for the pilot.	2/5 in TMD
High	Tasks triggered by high complexity of operational conditions are many and/or somewhat difficult, equating to considerable load for the pilot.	3/5 in TMD
Very high	Tasks triggered by very high complexity of operational conditions are high in number and/or difficult, equating to intensive load for the pilot.	4/5 in TMD
Extreme	Tasks triggered by extreme complexity of operational conditions are excessive and/or very difficult, equating to intolerable load for the pilot.	5/5 in TMD

Table 4
Correlation between environmental complexity and TMD.

Environmental complexity (η_{EC})	Description	Correlation with TMD
Low	Tasks triggered by low complexity of environmental conditions are very few and/or very easy, equating to none or very little load for the pilot.	1/5 in TMD
Moderate	Tasks triggered by moderate complexity of environmental conditions are limited in number and/or fairly easy, equating to average load for the pilot.	2/5 in TMD
High	Tasks triggered by high complexity of environmental conditions are many and/or somewhat difficult, equating to considerable load for the pilot.	3/5 in TMD
Very high	Tasks triggered by very high complexity of environmental conditions are high in number and/or difficult, equating to intensive load for the pilot.	4/5 in TMD
Extreme	Tasks triggered by extreme complexity of environmental conditions are excessive and/or very difficult, equating to intolerable load for the pilot.	5/5 in TMD

• System and interface variables

The only system/interface variable assumed for our CPAI verification case study is the Automation Level (AL).

χ_{AL} = **automation level:** represents the level of assistance provided by CPAI to the pilot to maintain his/her cognitive states in a certain range.

4.2. CPAI models

The simulation comprises of three components including task mental demand estimation, pilot cognitive states estimation and CPAI decision logics.

4.2.1. Task mental demand models

Based on the various levels of operational and environmental complexity, one or more tasks are triggered and they vary in difficulty, which contribute to different levels of workload. Assumed correlations between operational complexity, environmental complexity and Task Mental Demand (TMD) are described in Tables 3 and 4.

4.2.2. Mental fatigue estimation based on external conditions

In our research, mental fatigue is cumulative in relation to the task mental demand. The Rate of Change in MFA coefficient (ROC_{MFA}) is assumed to be linearly proportional to the TMD. The coefficients for this linear fit were determined based on the following conditions:

$$ROC_{MFA} = 1 \text{ in 30 minutes if the } TMD = 1 \quad (7)$$

$$ROC_{MFA} = -0.5 \text{ in 30 minutes if the } TMD = 0 \quad (8)$$

Therefore, the mental fatigue related to TMD (ψ''_{MFA}) are described as

$$\psi''_{MFA}(t) = 1.5\ TMD - 0.5 \quad (9)$$

$$\psi''_{MFA}(t_i) = \int_0^{t_i} \psi''_{MFA}(t)dt \quad (10)$$

4.2.3. Cognitive states estimation based on physiological measurement

Cognitive indicators provided in our research include MWL coefficient and MFA coefficient. As mentioned in Section 3.1, each cognitive indicator coefficient ψ_j consists of two parts: real-time pilot cognitive states based on physiological measurements ψ'_j and estimates based on external conditions ψ''_j, which are described as

$$\psi_{MWL} = \delta_m\ \psi'_{MWL} + \delta_e\ \psi''_{MWL} \quad (11)$$

$$\psi_{MFA} = \delta_m\ \psi'_{MFA} + \delta_e\ \psi''_{MFA} \quad (12)$$

• Mental workload

Studies have shown that heart and respiratory rates increase while the blink rate decreases with increases in mental workload [2,8,47]. However, the physiological measurables of people in different age groups vary widely. Based on the literature, the reference value (as the typical value for resting adult) of heart rate, respiratory rate and blink rate are assumed as 73 bpm, 16 brpm and 18 tpm respectively [2]. The operational limit value of HR, RR and BR are assumed as 90 bpm, 33 brpm and 3 tpm [55].

Table 5 illustrates assumed correlations between physiological measurables and MWL coefficient.

In our research, all relationships between physiological measurables and MWL coefficient are assumed to be linear. According to Table 5, the correlations are defined as:

$$\psi'_{MWL/HR,t} = 0.059\varphi_{HR} - 4.3 \quad (13)$$

$$\psi'_{MWL/RR,t} = 0.06\varphi_{RR} - 0.96 \quad (14)$$

$$\psi'_{MWL/BR,t} = -0.067\varphi_{BR} + 1.2 \quad (15)$$

~~Each physiological parameter in the process of estimation has a weight factor reflecting the parameter importance level.~~ According to the experimental data from the human factors research group in Shanghai Jiao Tong University [56], the weight of heart rate contributing to workload was highest while the blink interval was the

Table 5
Correlation between physiological measurables and MWL coefficient.

Physiological parameters	Value	MWL coefficient	Description
Heart rate (bpm)	73	0	Rest
	78∼80	0.3∼0.4	Optimal
	90	1	Assumed operational limit
Respiratory rate (brpm)	16	0	Rest
	21∼23	0.3∼0.4	Optimal
	33	1	Assumed operational limit
Blink rate (tpm)	18	0	Rest
	13∼12	0.3∼0.4	Optimal
	3	1	Assumed operational limit

Table 6
Correlation between physiological measurables and MFA coefficient.

Physiological parameters	Value	MFA coefficient	Description
Heart rate (bpm)	73	0	Optimal
	90	1	Assumed operational limit
Blink rate (tpm)	18	0	Optimal
	36	1	Assumed operational limit

lowest. As a result, the weights for heart rate, respiratory rate and blink rate in the simulation are assumed to be 0.5, 0.3 and 0.2 and therefore, the value of mental workload related to detected physiological states are presented as:

$$\psi'_{MWL} = 0.5\ \psi'_{MWL/HR} + 0.3\ \psi'_{MWL/RR} + 0.2\ \psi'_{MWL/BR} \tag{16}$$

- Mental fatigue

Mental fatigue leading to critical errors and decreased performance is inevitable for the pilot during the flight. It is found that higher heart rates are related to higher fatigue levels and the blink rate demonstrates a similar relationship. Consequently, we assumed that the relationship between the mental fatigue and heart rate and blink rate are both linearly increasing in the simulation and the weight assigned to two parameters are equal. Table 6 shows the correlation between physiological measurables and MFA coefficient.

Similar to the MWL coefficient, the relationships between physiological measurables and mental fatigue are assumed to be linear, which are described as:

$$\psi'_{MFA/HR,t} = 0.059\ \varphi_{HR} - 4.3 \tag{17}$$

$$\psi'_{MFA/BR,t} = 0.056\ \varphi_{BR} - 1 \tag{18}$$

For mental fatigue, heart rate is more important than blink rate and this is reflected in the weighting of the two parameters, respectively assumed to be 0.6 and 0.4. The mental workload is modelled as a function of the detected physiological states as:

$$\psi'_{MFA} = 0.6\ \psi'_{MFA/HR} + 0.4\ \psi'_{MFA/BR} \tag{19}$$

4.2.4. Human-machine task allocation based on automation levels

Based on the LOA scale proposed by Sheridan et al. [48], an adapted LOA scale for CPAI is introduced in Table 7. The defined automation levels range from one to seven. Automation level one implies that the pilot retains full control of the aircraft and automation provides no assistance at all. In the subsequent three automation levels (2 to 4), CPAI provides to the pilot a number of determined decisions/actions that are based on the pilot's estimated mental workload and fatigue levels. In the subsequent automation levels, CPAI progressively relinquishes the execution responsibility from the pilot, up to full automation. Additionally, an assumed allocation of task load between the human operator and the machine is introduced. In particular, from level 1 to level 5, the pilot is required to make the final decision based on the different amount of provided selections and the human task load declines with the decreased number of options. At automation level 6, the human task load significantly falls to 30%, as the pilot only has to monitor the decisions made by machine. Level 7 is only triggered by pilot incapacitation, so systems are allocated 100% load at this level.

4.2.5. CPAI decision logics

Two decision tables were developed to implement the reconfiguration logics of CPAI. In Table 8, the automation level changes based on the different MWL coefficients and the active automation levels. The optimal range of MWL coefficient lies between 0.3 and 0.4. The automation level decreases to varying degrees if the WL coefficient is less than 0.3 (to prevent the negative effects of underloading the pilot) while the automation level increases if the WL coefficient exceeds 0.4 (to prevent the negative effects of overloading the pilot). In normal operations, the adjustment is between automation level 1 and level 6. Level 7 is activated as a special case for emergency scenarios (e.g. pilot incapacitation) and once triggered is always maintained unless an intervention by any human operator incurs.

Table 9 illustrates the change of automation levels based on the different MFA coefficients and the active automation levels. It is recognized that mental fatigue contributes to significantly degrading performance and therefore, the adjustment of automation level aims to minimize the mental fatigue. Similar to the MWL decision table, the MFA drives changes in automation lever between level 1 and level 6. Level 7 is activated in emergencies and once triggered is always maintained unless an intervention by any human operator incurs.

After the two potentially different automation levels are separately calculated according to the decision logics accounting for MWL and MFA coefficients respectively, CPAI automatically selects the higher automation level as the final output. This selection is mathematically described as:

$$\chi_{AL} = max\left(\chi_{AL/MWL}, \chi_{AL/MFA}\right) \tag{20}$$

Where $\chi_{AL/MWL}$ represents the automation level determined based on MWL coefficient and $\chi_{AL/MFA}$ is the automation level determined based on MFA coefficient.

Table 7
Levels of automation and human-machine task allocation (adapted from [48]).

Automation level	Automation description	Primary responsible for execution of tasks	Machine task load	Human task load
1	The CPAI offers no assistance: the pilot must make all decisions and perform all actions	Pilot	0	100%
2	The CPAI provides to the pilot a complete set of decision/ action alternatives	Pilot	10%	90%
3	The CPAI provides to the pilot a few optimal decisions/ actions from the complete set of alternatives	Pilot	20%	80%
4	The CPAI identifies the best decision/action and recommends it to the pilot	Pilot	30%	70%
5	The CPAI identifies the best decision/action, recommends it to the pilot, configures the aircraft and commands the execution upon pilot approval	Automation systems	40%	60%
6	The CPAI identifies the best decision/action, configures the aircraft, commands the execution and informs the pilot	Automation systems	70%	30%
7	The CPAI identifies the best decision/action, commands it to the aircraft and informs ATCo and AOC operator and subsequently the pilot if and when requested.	Automation systems	100%	0

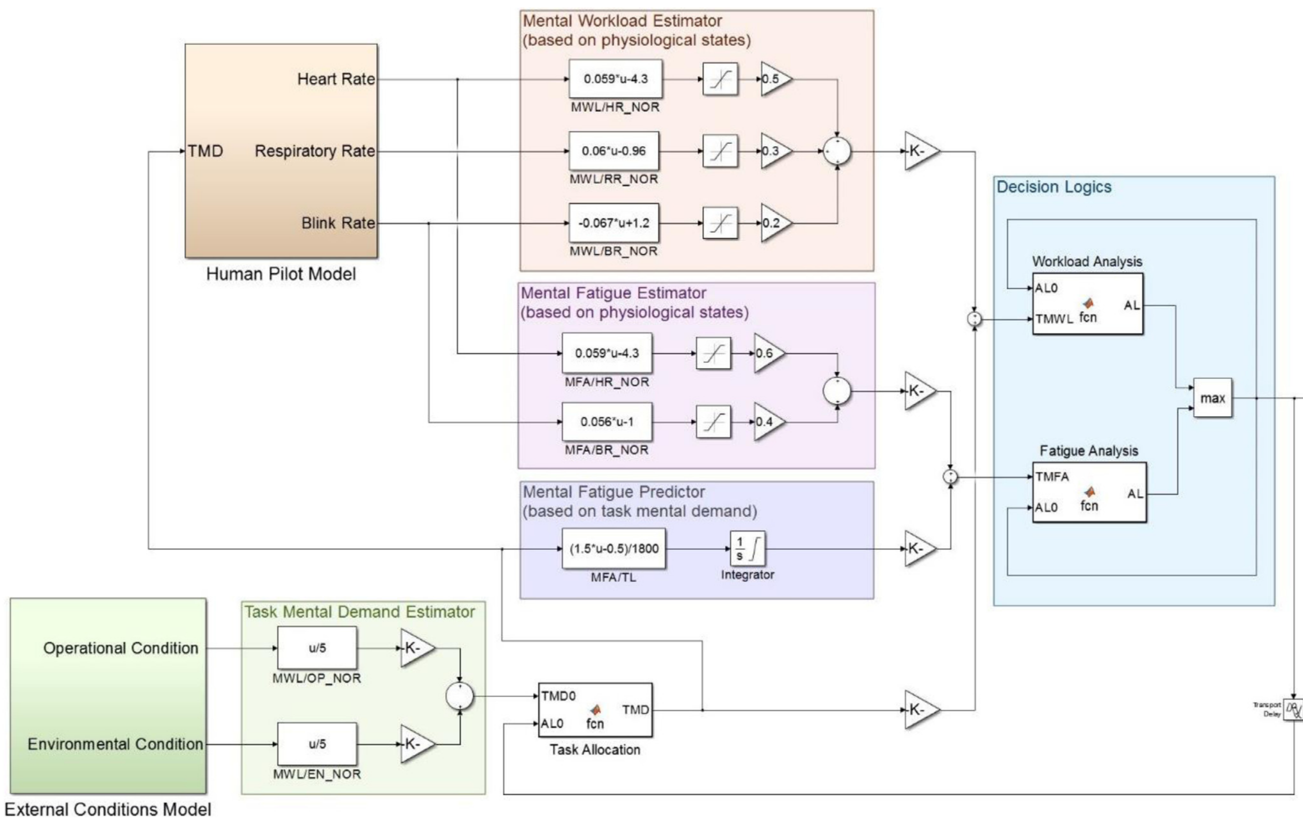


Fig. 9. CPAI numerical simulation layout.

Table 8
CPAI decision logics related to MWL coefficient.

Range of MWL Values	Automation level ($\chi_{AL/MWL}$)						
	1	2	3	4	5	6	7
$\psi_{MWL} \le 0.2$	2	2	2	2	2	2	7
$0.2 < \psi_{MWL} \le 0.4$	3	3	3	3	3	3	7
$0.4 < \psi_{MWL} \le 0.6$	3	3	3	4	4	4	7
$0.6 < \psi_{MWL} \le 0.8$	5	5	5	5	5	5	7
$0.8 < \psi_{MWL}$	6	6	6	6	6	6	7

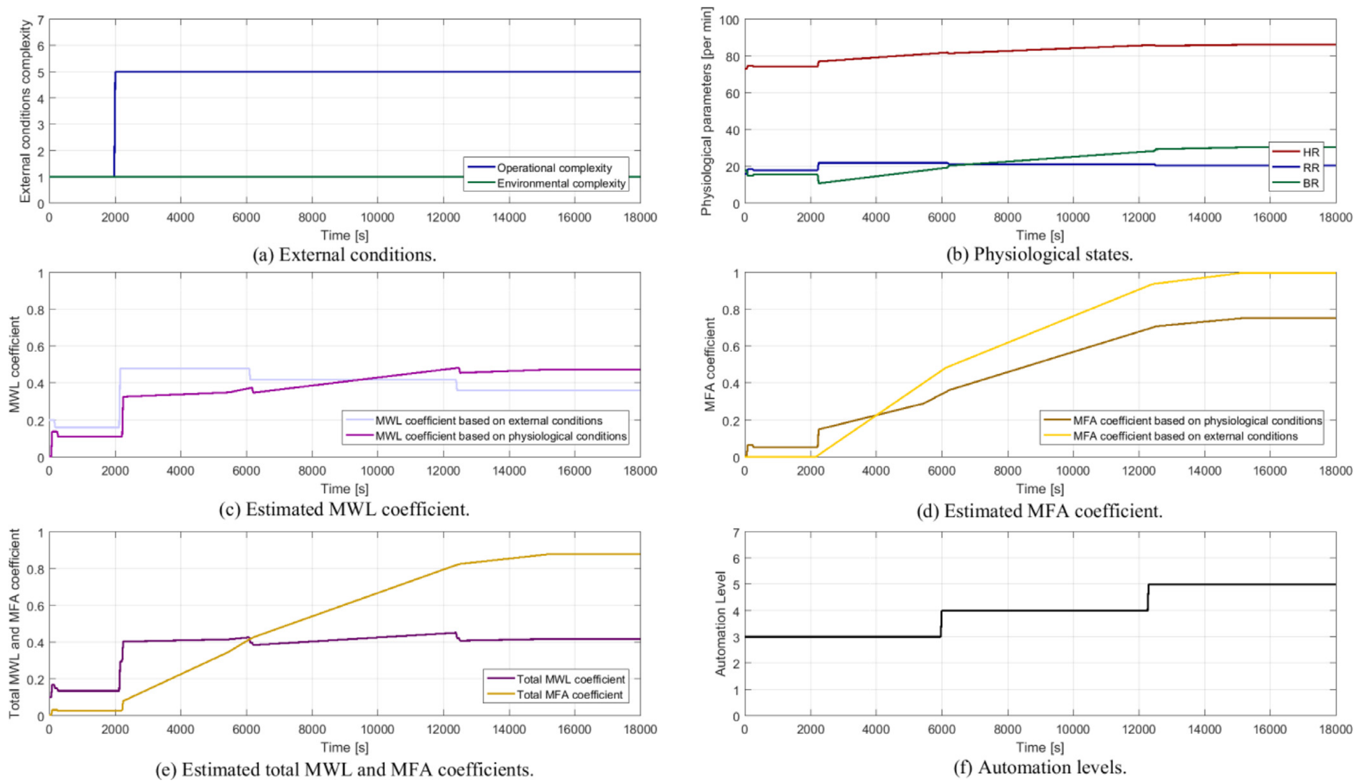
Table 9
CPAI decision logic related to MFA coefficient.

Range of MFA values	Automation level ($\chi_{AL/MFA}$)						
	1	2	3	4	5	6	7
$\psi_{MFA} \le 0.4$	1	2	3	3	3	3	7
$0.4 < \psi_{MFA} \le 0.8$	4	4	4	4	4	4	7
$0.8 < \psi_{MFA} \le 0.9$	5	5	5	5	5	5	7
$0.9 < \psi_{MFA}$	6	6	6	6	6	6	7

4.2.6. Simulation layout and results

Fig. 9 illustrates the CPAI numerical simulation layout in MATLAB/Simulink. The inputs of the model include two external condition parameters: the operational complexity and the environmental complexity. The output is the automation level defined in Section 4.2. The purpose of the performed simulation case studies is to preliminarily validate the feasibility of CPAI models.

The preliminary verification addresses simplified cases to ensure that no error is present in the software. Following the preliminary verification, some simulation case studies in representative conditions are conducted to evaluate the CPAI model.



(a) External conditions.
(b) Physiological states.
(c) Estimated MWL coefficient.
(d) Estimated MFA coefficient.
(e) Estimated total MWL and MFA coefficients.
(f) Automation levels.

Fig. 10. Preliminary verification results involving a step increase in operational complexity only.

4.2.7. Preliminary model verification

Three preliminary verification case studies were implemented to evaluate the CPAI operation in worst-case conditions and verify the implemented models.

(A) **Step increase in one external condition:** the operational and environmental complexities are both low and constant at the start of the simulation (level 1). At 2000 s, there is a step increase to a very high level of operational complexity (from level 1 to level 5) while the environmental complexity remains unaltered. Fig. 10 depicts the results of this verification case. Around 2100 s, the physiological variables capture the surge of operational complexity, which is propagated to the cognitive state estimates. However, the automation level only increases at 6000 s because the workload is affordable to the pilot during the previous period. At 6000 s, the increasing MFA triggers a variation in automation level, which is increased to level 4 as a response to the overload. Due to the continuously very high level of operational complexity, MFA keeps increasing, though at a lower rate. This triggers an increase in the automation level to level 5 at around 12,200 s according to the task allocation logics, so that the pilot's workload experiences slight drops at 6000 s and 12,200 s (Fig. 10). The total MFA estimate stabilises at 0.9.

(B) **Step increase in both external conditions:** both operational and environmental complexity parameters start low and constant (level 1). At 2000 s, there is a step increase to a very high level for both of them (from level 1 to level 5). Fig. 11 depicts the results of this verification case. Differently from verification case A, the automation is increased to level 5 very rapidly in this case as the pilot cannot afford the very high cognitive load caused by the surge of both external conditions. From 2000 s to 6000 s, the automation level oscillates between levels 4 and 5, as MWL fluctuates about 0.6. Eventually, fatigue builds up and MFA becomes the dominant determinant in the system. This causes both automation level and MWL to stabilise at level 5 from 6000 s onwards. Compared to verification case A, the automation level changed faster and greater in this case. The short fluctuations between levels 4 and 5 in the initial stages of the simulation show that the system's transient response is highly dependent on MWL, while MFA dynamics mainly drive its steady state behaviour (Fig. 11).

(C) **Periodic variations of external conditions:** operational and environmental complexities fluctuate regularly with a frequency of 2.8×10^{-4} hz (1 peak/ hour), from levels 1 to 5. The variation in estimated MWL is consistent with the periodic variations of external conditions. As shown in Fig. 12 (a and c), in the half-period between 0 and 1700 s, the increase in external conditions from level 1 to 5 drives an increase in the MWL coefficient from 0 to 0.7. From 2500 s to 4000 s, the estimated MWL coefficient declines to 0.17, together with the decreasing external condition complexity. This trend repeats in the following periods. The MFA coefficient increases gradually due to its cumulative characteristic. At around 10,000 s, the total MFA estimate stabilises around 0.9 due to the increasing periods characterised by automation level 5 (Fig. 12d). The changes of detected heart rate, respiratory rate and blink rate (Fig. 12b) indicate that the human pilot experiences different levels of mental workload and fatigue (Fig. 12c and d). In particular, the short-period oscillations of heart, respiratory and blink rate are correlated to MWL. Blink rate shows an inverse correlation, being a half-period out of phase with MWL. During the half-period between 0 and 1700 s, the MWL coefficient gradually grows to 0.7 while the HR, RR and BR are change from 73 to 82 bpm, 16 to 25 brpm and 18 to 9 tpm respectively. However, from 1800 s to 4000 s, when the MWL coefficient de-

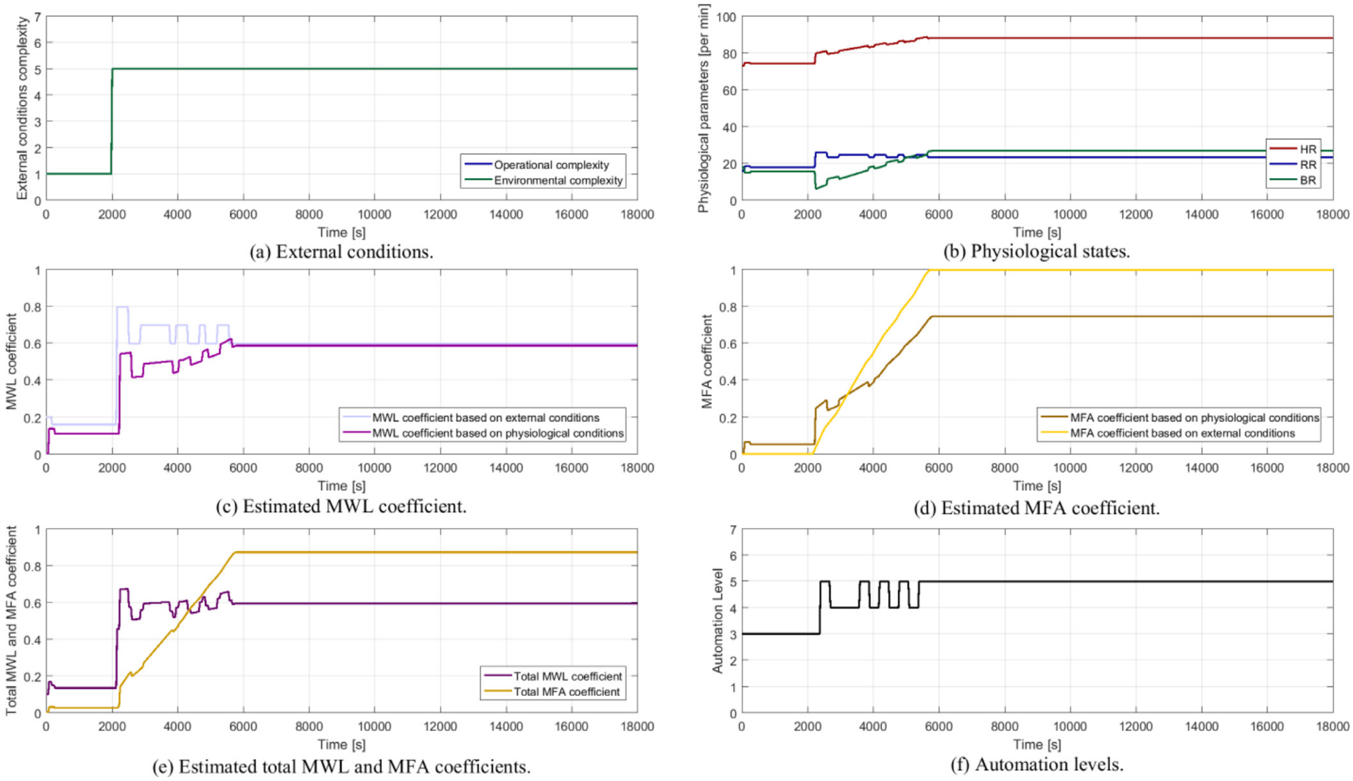


Fig. 11. Preliminary verification results involving a step increase in both external conditions.

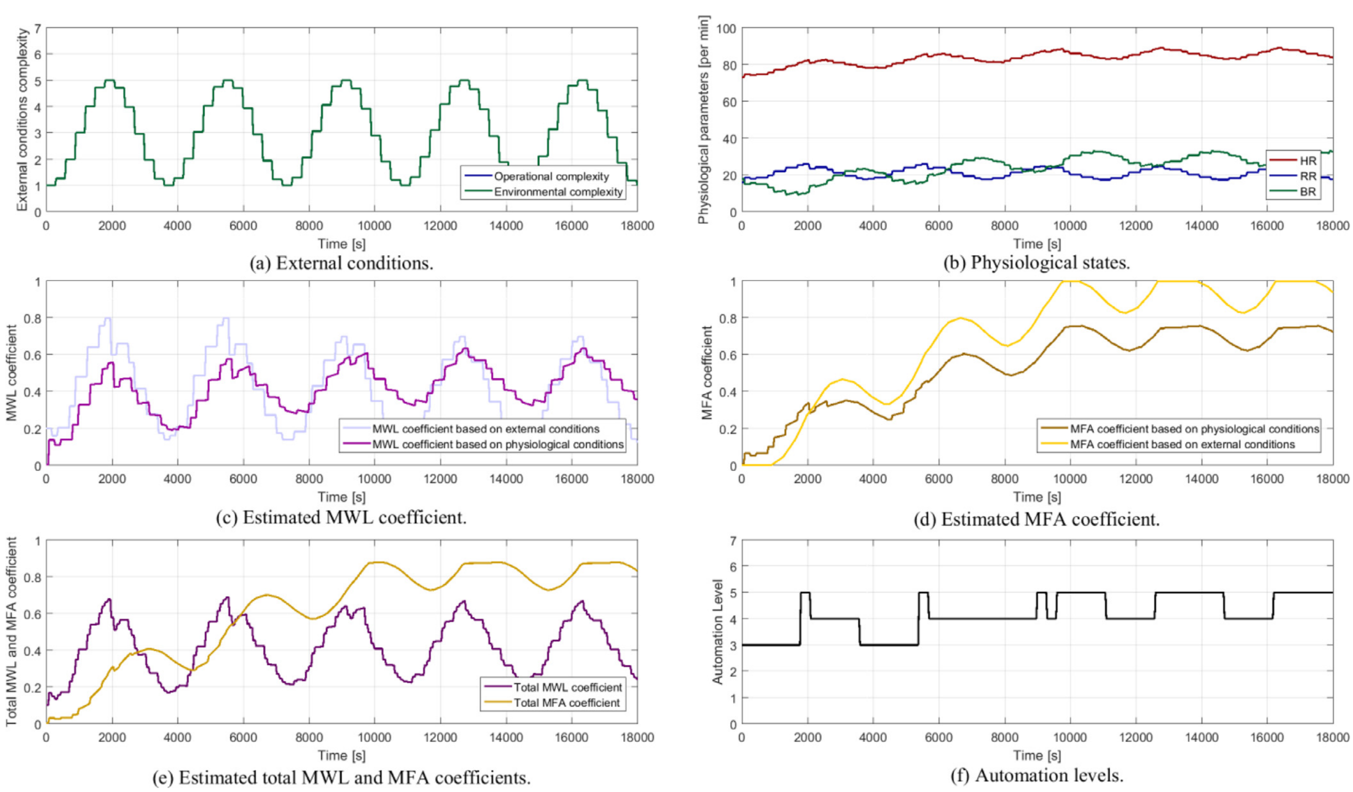
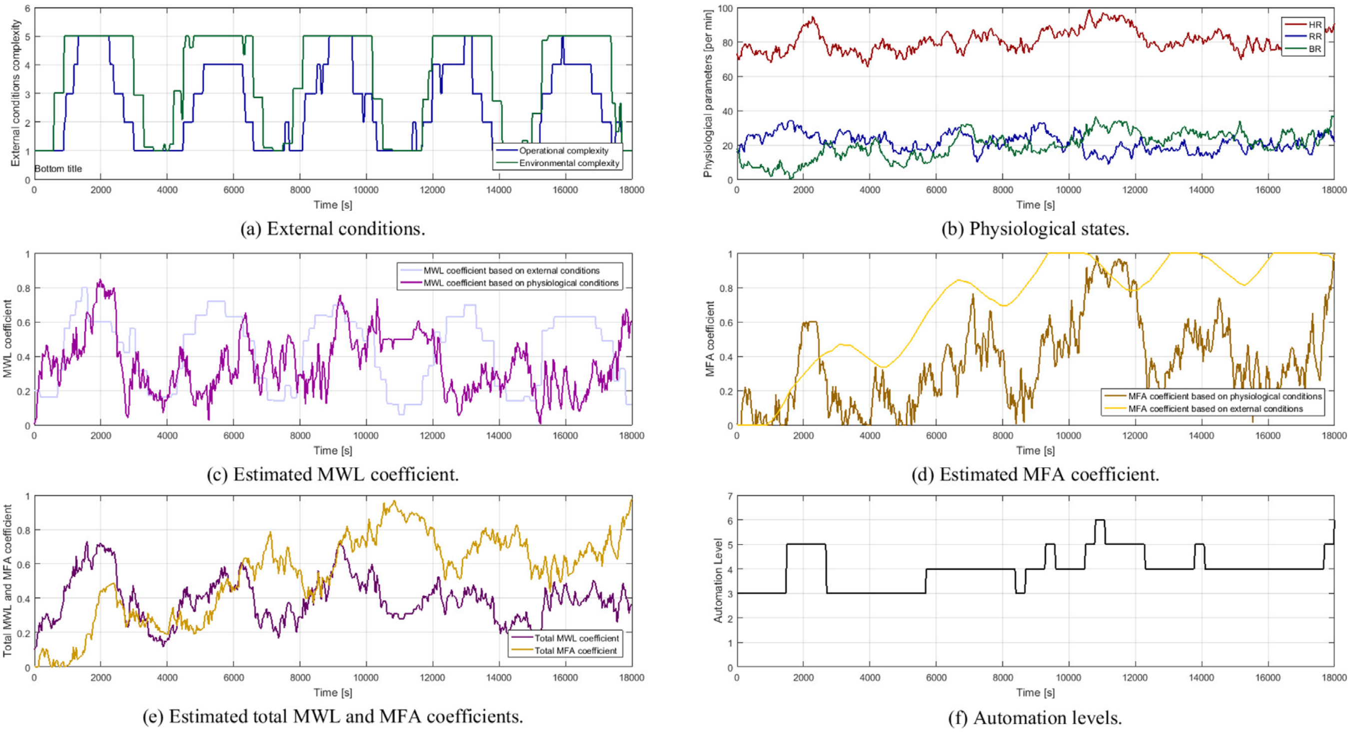


Fig. 12. Results for simulation with periodic variations of external conditions.



(a) External conditions. (b) Physiological states.

(c) Estimated MWL coefficient. (d) Estimated MFA coefficient.

(e) Estimated total MWL and MFA coefficients. (f) Automation levels.

Fig. 13. Results for simulation with added sensor noise.

creases to 0.17, the physiological measurables undergo a corresponding change, with HR, RR and BR reverting to 78 bpm, 18 brpm and 22 tpm respectively. Similar variations occur in the following oscillation cycles. On the other hand, MFA shows an overall upward periodic trend associated with its cumulative characteristic, except that the fluctuations are phase-shifted by approximately 700 s to 1200 s. The result of increasing fatigue is captured by the heart and blink rates, which show a gradual increase over time. Fig. 12f illustrates the shifts in automation level. The automation levels increase to level 5 at around 2000 s as the systems infers that the pilot is overloaded (with a MWL coefficient of approximately 0.7). Shortly after, the automation level decreases to level 4 due to the decrease of total MWL coefficient and the low total MFA coefficient. The automation further decreases to level 3 at 3500 s, before undergoing a sharp increase at 5500 s when the external complexity peaks. The automation then quickly drops back to level 4 and remains constant until 9000 s. It does not revert to level 3 as fatigue is now moderately high. From 9000 s to 18,000 s, the automation fluctuates between automation levels 4 and 5 due to the changes in total MWL and MFA coefficient. An MFA estimate exceeding 0.8 indicates that the human pilot is experiencing a significant fatigue, which engages a high automation level (level 6) to avoid fatigue-induced human errors. Soon afterwards, the human pilot slowly recovers due to the substantial load (70%) shared by machine and to the decreasing external complexity.

The preliminary verification case studies demonstrate the CPAI operation in worst-case conditions. The estimated human cognitive states (MWL and MFA levels) change according to external conditions and are always consistent with detected physiological variables. CPAI provides an automatically modulated task distribution to keep the human working in a certain range of workload and a minimum fatigue levels, which leads to optimal performance.

4.2.8. Simulation with added noise

The data acquired by CPAI using a combination of both wearable and non-contact devices is degraded due to various factors including measurement noise, interference from body movement, improper fastening (for wearable devices), as well as sensor outages. Based on the literature, the extent of this degradation in data acquisition typically falls within the range of 5% to 30% [16,18,22,36]. To evaluate the impact of this degradation, an uncertainty analysis was performed by injecting a normally distributed noise with a standard deviation of $\sigma_i = 0.3\,\varphi_i$ in the three physiological input variables and a uniformly distributed noise of $\sigma_i = 0.15\,\varphi_i$ in external conditions and the results were compared to verification case C described in section 4.2.7. The results of this analysis are depicted in Fig. 13. Due to the added noise, there are significant deviations in the physiological estimation of the MWL and MFA coefficients, which affect the final MWL and MFA values. A limited phase shift between MWL and MFA is evident from 0 s to 6000 s in Fig. 12e, but from 6000 s onwards MFA coefficient shows a large tendency to be inversely correlated to MWL. The uncertainties in MFA and MWL estimates are only partially propagated to the automation level. From 0 s to 10,000 s, the automation level is largely similar to Fig. 12f. From 10,000 s to 18,000 s, the automation level is less responsive to external conditions and does not oscillate in the same sinusoidal manner as verification case C.

Even though sensor noise introduces a greater degree of uncertainty in the system, the overall effectiveness of the CPAI processing and system reconfiguration logics is ultimately not compromised. The system's robustness can be seen as CPAI successfully infers a net increase in MWL and MFA and increases the AL on average as a result. At high fatigue levels, the system becomes largely dependent on blink rate, as high blink rate is a key indicator of fatigue. As a result, the uncertainty of the system output states at this stage will be dependent on the uncertainty in blink rate measurement. This reliance can be mitigated with a dynamic weighting algorithm. This algorithm dynamically adjusts the weights of external and physiological conditions, as well as the system design parameters included in the sensing, estimation and reconfiguration modules based on significant changes in the covariance between system parameters. As a result, the effect of measurement noise on the system can be reduced. Further research will explore the optimal selection of weightings and system design parameters that maximise noise-resilience of the CPAI system and will also investigate the integration of a dynamic weighting algorithm.

5. Conclusion and future work

The conceptual design, development and preliminary verification of a Cognitive Pilot-Aircraft Interface (CPAI) system for Single-Pilot Operations (SPO) were presented. A three-step CPAI working process including physiological sensing, cognitive state estimation and system reconfiguration was developed to achieve optimal pilot-aircraft interactions and prevention of human pilot errors. Six layers of variables were introduced in the CPAI working process, including physiological, operational, environmental, cognitive, system and interface parameters. In order to implement the CPAI system, a preliminary prototype using a subset of variables (including three physiological measurables, two cognitive indicators, two external condition variables and one system reconfiguration variable) was numerically assessed through representative simulation case studies. The simulation results demonstrate the technical feasibility of the CPAI system concept. Specifically, the estimated human cognitive states are consistent with both the external conditions and the detected physiological states. The CPAI system is unique in that the expert decision logics, which introduce adaptivity into the avionics Human-Machine Interface (HMI), are driven by estimations of the pilot's cognitive states. The range of optimal performance is defined in terms of pilot's workload and fatigue levels, which are moderated by reallocating the task-load with varying levels of automation. Future research will assess the potential of other measurable physiological parameters such as brain activity electrical/thermal signatures, heart rate variability, pupil diameter and skin temperature as well as other cognitive indicators such as stress and attention levels. Individual differences such as personality types and experience affecting the pilot's capabilities will be also investigated. The experimental campaign will include task-based Pilot-In-The-Loop (PITL) experiments performed as part of the research collaboration in place with Express Freighters Australia (EFA) and the QANTAS Flight Training Centre.

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References

[1] AIRBUS, Standard Operating Procedures-Operating Philosophy, Airbus, France, 2006.
[2] J.L. Andreassi, Psychophysiology: Human Behavior & Physiological Response, Psychology Press, 2013.
[3] P. Aricò, G. Borghini, I. Graziani, et al., 'Air-traffic-controllers (ATCO): neurophysiological analysis of training and workload', Ital. J. Aerosp. Med. 2015 (2015) 35.
[4] H. Ayaz, B. Onaral, K. Izzetoglu, et al., 'Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: empirical examples and a technological development', Front. Hum. Neurosci. 7 (2013) 871, doi:10.3389/fnhum.2013.00871.
[5] H. Ayaz, P.A. Shewokis, S. Bunce, et al., 'Optical brain monitoring for operator training and mental workload assessment', Neuroimage 59 (1) (2012) 36–47.
[6] C. Berka, D.J. Levendowski, M.M. Cvetinovic, et al., 'Real-time analysis of EEG indexes of alertness, cognition, and memory acquired with a wireless EEG headset', Int. J. Hum. Comput. Interact. 17 (2) (2004) 151–170.
[7] B. Billiere, T. Dautermann, J. Dokic, et al. 2013, *ACROSS: validation plan*, ACROSS Consortium.
[8] G. Borghini, L. Astolfi, G. Vecchiato, et al., 'Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness', Neurosci. Biobehav. Rev. 44 (2014) 58–75.
[9] K.A. Brookhuis, D. de Waard, 'Monitoring drivers' mental workload in driving simulators using physiological measures', Accid. Anal. Prev. 42 (3) (2010) 898–903.
[10] B.K. Burian, S. Pruchnicki, J. Rogers, et al. 2013, *Single-pilot workload management in entry-level jets*, DTIC Document.
[11] R.D. Campbell, M. Bagshaw, Human Performance and Limitations in Aviation, John Wiley & Sons, 2008.
[12] D. Comerford, S.L. Brandt, J.B. Lachter, et al., NASA's single-pilot operations technical interchange meeting: proceedings and findings, NASA's Single-Pilot Operations Technical Interchange Meeting, 2013.
[13] Croft, NASA Advances Single-Pilot Operations Concepts. http://aviationweek.com/technology/nasa-advances-single-pilot-operations-concepts, 2015 (accessed 07.09.16).
[14] L.L. Di Stasi, A. Antolí, M. Gea, et al., A neuroergonomic approach to evaluating mental workload in hypermedia interactions, Int. J. Ind. Ergon. 41 (3) (2011) 298–304, doi:10.1016/j.ergon.2011.02.008.
[15] Doyle A. 2010, 'Embraer reveals vision for single-pilot airliners', *Flightglobal*.
[16] F. El-Amrawy, M.I. Nounou, Are currently available wearable devices for activity tracking and heart rate monitoring accurate, precise, and medically beneficial? Healthcare Inf. Res. 21 (4) (2015) 315–320.
[17] K.K.E. Ellis, Eye tracking metrics for workload estimation in flight deck operations, Master of Science Thesis, University of Iowa, 2009.
[18] K.R. Evenson, M.M. Goto, R.D. Furberg, 'Systematic review of the validity and reliability of consumer-wearable activity trackers', Int. J. Behav. Nutr. Phys. Act. 12 (1) (2015) 1–22.
[19] FAA, 120-71A - Standard Operating Procedures for Flight Deck Crewmembers, Federal Aviation Administration, USA, 2003.
[20] FAA, Pilot's Handbook of Aeronautical Knowledge, Federal Aviation Administration (FAA), Oklahoma, USA, 2008.
[21] K.M. Feigh, M.C. Dorneich, C.C. Hayes, 'Toward a characterization of adaptive systems a framework for researchers and system designers', Hum. Factors 54 (6) (2012) 1008–1024.
[22] T. Ferguson, A.V. Rowlands, T. Olds, et al., 'The validity of consumer-level, activity monitors in healthy adults worn in free-living conditions: a cross-sectional study', Int. J. Behav. Nutr. Phys. Act. 12 (1) (2015) 42.
[23] A. Gardi, R. Sabatini, T. Kistan, et al., '4 Dimensional trajectory functionalities for air traffic management systems', 15th Integrated Communication, Navigation and Surveillance Conference, ICNS 2015, 2015, doi:10.1109/ICNSURV.2015.7121246.
[24] V.J. Gawron, Human performance, in: Human Performance, Workload, and Situational Awareness Measures Handbook, Second Edition, CRC Press, 2008, pp. 13–86.
[25] L. Giraudet, J.P. Imbert, M. Bérenger, et al., The neuroergonomic evaluation of human machine interface design in air traffic control using behavioral and EGG/ERP measures, Behav. Brain Res. 294 (2015) 246–253, doi:10.1016/j.bbr.2015.07.041.
[26] J.A. Healey, R.W. Picard, Detecting stress during real-world driving tasks using physiological sensors, Intell. Transp. Syst. IEEE Trans. 6 (2) (2005) 156–166.
[27] A. Hoover, A. Singh, S. Fishel-Brown, et al., Real-time detection of workload changes using heart rate variability, Biomed. Signal Process. Control 7 (4) (2012) 333–341, doi:10.1016/j.bspc.2011.07.004.
[28] M. Hou, R.D. Kobierski, M. Brown, Intelligent adaptive interfaces for the control of multiple UAVs, J. Cognit. Eng. Decis. Making 1 (3) (2007) 327–362.
[29] ICAO, Global and Regional 20-year Forecasts, ICAO, Montreal, Canada, 2011.
[30] T. Inagaki, Adaptive automation: sharing and trading of control, Handb. Cognit. Task Des. 8 (2003) 147–169.
[31] A. Isaac, S.T. Shorrock, R. Kennedy, et al. Technical review of human performance models and taxonomies of human error in ATM (HERA), *European Air Traffic Management Programme (EATMP)*, 2002.
[32] W. Johnson, J. Lachter, M. Feary, et al., Task allocation for single pilot operations: a role for the ground, in: International Conference on Human-Computer Interactions in Aerospace, HCI Aero 2012, 2012.
[33] JPDO, Concept of Operations for the Next Generation Air Transportation System. Version 3.2 (2011).
[34] D.B. Kaber, M.R. Endsley, Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety, Process Saf. Progr. 16 (3) (1997) 126–131.
[35] D.B. Kaber, J.M. Riley, K.-W. Tan, et al., On the design of adaptive automation for complex systems, Int. J. Cognit. Ergon. 5 (1) (2001) 37–57.
[36] J.-M. Lee, Y. Kim, G.J. Welk, Validity of consumer-based physical activity monitors, Med. Sci. Sports Exerc. 46 (9) (2014) 1840–1848.
[37] Liu K.K.-L. 2004, 'A personal, mobile system for understanding stress and interruptions', Massachusetts Institute of Technology.
[38] L. Liu, Y. Peng, M. Liu, et al., Sensor-based human activity recognition system with a multilayered model using time series shapelets, Knowl. Based Syst. 90 (2015) 138–152.
[39] C.A. Miller, M.D. Hannen, The Rotorcraft Pilot's Associate: design and evaluation of an intelligent user interface for cockpit information management, Knowl. Based Syst. 12 (8) (1999) 443–456.

[40] N.M. Moacdieh, J.C. Prinet, N.B. Sarter, Effects of modern primary flight display clutter evidence from performance and eye tracking data, in: Proceedings of the Human Factors and Ergonomics Society annual meeting, 2013.
[41] P. Pandian, K. Mohanavelu, K. Safeer, et al., Smart vest: wearable multi-parameter remote physiological monitoring system, Med. Eng. Phys. 30 (4) (2008) 466–477.
[42] R. Parasuraman, V. Riley, Humans and automation: use, misuse, disuse, abuse, Hum. Factors 39 (2) (1997) 230–253.
[43] S. Ramasamy, R. Sabatini, A. Gardi, Novel flight management system for improved safety and sustainability in the CNS+A context, 15th Integrated Communication, Navigation and Surveillance Conference, ICNS 2015, 2015, doi:10.1109/ICNSURV.2015.7121225.
[44] R. Sabatini, T. Moore, C. Hill, A new avionics-based GNSS integrity augmentation system: part 1–fundamentals, J. Navig. 66, (03) (2013) 363–384, doi:10.1017/S0373463313000027.
[45] R. Sabatini, T. Moore, C. Hill, A new avionics-based GNSS integrity augmentation system: part 2–integrity flags, J. Navig. 66 (04) (2013) 501–522, doi:10.1017/S0373463313000143.
[46] G. Salvendy, Handbook of Human Factors and Ergonomics, John Wiley & Sons, 2012.
[47] C. Schulz, E. Schneider, L. Fritz, et al., Eye tracking for assessment of workload: a pilot study in an anaesthesia simulator environment, Br. J. Anaesthesia 106 (1) (2011) 44–50.
[48] T.B. Sheridan, Adaptive automation, level of automation, allocation authority, supervisory control, and adaptive control: distinctions and modes of adaptation, Syst. Man Cybern. Part A IEEE Trans. 41 (4) (2011) 662–667, doi:10.1109/TSMCA.2010.2093888.
[49] C. Shyh-Yueh, L. Chao-Chen, C. Jia-Jin, fNIRS and EEG study in mental stress arising from time pressure, in: Advances in Cognitive Engineering and Neuroergonomics, CRC Press, 2012, pp. 249–258.
[50] C.R. Spitzer, U. Ferrell, T. Ferrell, Digital Avionics Handbook, CRC Press, 2014.
[51] L.G. Terveen, Overview of human-computer collaboration, Knowl. Based Syst. 8 (2) (1995) 67–81.
[52] U.S. Air Force, Report on Technology Horizons, a Vision for Air Force Science and Technology During 2010–2030, United States Air Force, 2010 AF/ST-TR-10-01-PR, Retrieved from http://www.af.mil/shared/media/document/AFD-100727-053.pdf .
[53] C.D. Wickens, J.G. Hollands, S. Banbury, et al., Engineering Psychology & Human Performance, Psychology Press, 2015.
[54] C.D. Wickens, J.D. Lee, Y. Liu, et al., Introduction to human factors engineering, second ed., Pearson, New Jersey, 2004.
[55] Y. Yao, Mental Workload Assessment in Military Pilots Using Psychophysiological Measures in Flight, Fourth Military Medical University, 2007.
[56] Y. Zhou, Research on Physiological Monitoring Technology for Aviation Human Factor Certification, Shanghai Jiao Tong University, 2013.
[57] E.M. Atkins, Certifiable Autonomous Flight Management for Unmanned Aircraft Systems, The Bridge 44 (3) (2014) 35–43.