aerospace

MDPI

Article

From Raw Data to Practical Application: EEG Parameters for Human Performance Studies in Air Traffic Control

María Zamarreño Suárez [1,*], Juan Marín Martínez [1], Francisco Pérez Moreno [1], Raquel Delgado-Aguilera Jurado [1], Patricia María López de Frutos [2] and Rosa María Arnaldo Valdés [1]

[1] Department of Aerospace Systems, Air Transport and Airports, School of Aerospace Engineering, Universidad Politécnica de Madrid (UPM), 28040 Madrid, Spain; juan.marin.martinez@alumnos.upm.es (J.M.M.); raquel.djurado@upm.es (R.D.-A.J.); rosamaria.arnaldo@upm.es (R.M.A.V.)

[2] ATM Research and Development Reference Centre (CRIDA), 28022 Madrid, Spain; pmldefrutos@e-crida.enaire.es

* Correspondence: maria.zamsuarez@upm.es

Abstract: The use of electroencephalography (EEG) techniques has many advantages in the study of human performance in air traffic control (ATC). At present, these are non-intrusive techniques that allow large volumes of data to be recorded on a continuous basis using wireless equipment. To achieve the most with these techniques, it is essential to establish appropriate EEG parameters with a clear understanding of the process followed to obtain them and their practical application. This study explains, step by step, the approach adopted to obtain six EEG parameters: excitement, stress, boredom, relaxation, engagement, and attention. It then explains all the steps involved in analysing the relationship between these parameters and two other parameters that characterise the state of the air traffic control sector during the development of real-time simulations (RTS): taskload and number of simultaneous aircraft. For this case study, the results showed the highest relationships for the engagement and attention parameters. In general, the results confirmed the potential of using these EEG parameters.

Keywords: air traffic control; human performance; human factors; electroencephalography; brain activity; parameters; software

check for updates

Citation: Zamarreño Suárez, M.; Marín Martínez, J.; Pérez Moreno, F.; Delgado-Aguilera Jurado, R.; López de Frutos, P.M.; Arnaldo Valdés, R.M. From Raw Data to Practical Application: EEG Parameters for Human Performance Studies in Air Traffic Control. *Aerospace* **2024**, *11*, 30. https://doi.org/10.3390/aerospace11010030

Academic Editor: Andreas Strohmayer

Received: 14 November 2023
Revised: 24 December 2023
Accepted: 27 December 2023
Published: 28 December 2023

1. Introduction

Air traffic controllers (ATCOs) perform tasks that are essential to the safety of air traffic management (ATM). The study of the human performance of these professionals has been a very important area of research due to the critical nature of their work. The ability of ATCOs to carry out their duties safely and efficiently is limited by their workload [1]. During the development of their activities, air traffic controllers are faced with a dynamic working environment, interacting with different technological tools and other professionals. During the performance of their tasks, they have to make critical decisions in very short time intervals and constantly monitor the actions implemented to anticipate future changes [2]. Therefore, the study of the workload of ATCOs and their human performance is one of the key principles of research in the interest of improving safety.

ATCOs' tasks depend on the flight phase of the aircraft for which they are responsible. The ATCOs responsible for the en-route phase of flight were the subject of this study. The objective of en-route air traffic control is to ensure the safe and orderly evolution of aircraft trajectories [3]. In this phase, aircraft fly through one or more sectors of the airspace, each of which is under the responsibility of one or more air traffic controllers.

The tasks to be performed by ATCOs in the en-route phase of flight include aircraft identification and takeover, identification and resolution of conflicts between aircraft, communication with pilots, and handover of aircraft to adjacent sectors. The ATCO's workload is usually a function of these tasks, which, at the same time, are a function of the number of simultaneous aircraft in the sector [4]. In this paper, both workload contributions were considered: a series of ATC events as a modelling of the actions performed by the ATCO and the number of simultaneous aircraft in the sector.

There are different types of techniques used to study the mental workload of ATCOs. Basically, there are three groups of techniques that can be used: the use of performance-based indicators, the use of subjective techniques, and the use of neurophysiological data [5]. Traditional techniques for assessing workload in situ at the workplace have involved the completion of questionnaires by ATCOs. More recently, however, techniques based on neurophysiological data have become more widely used. Although many of these techniques were initially confined to the medical field, in recent years, their application has expanded to include disciplines as diverse as ergonomics, marketing, and human performance evaluation [6]. The latter application was the focus of this study. This wide application is due to the development of big data processing techniques and the development of new portable sensors that do not restrict the subject's movement. These advances in technology have allowed new techniques to be explored and the use of neurophysiological techniques to increase.

There are examples of studies using eye-tracking techniques [7], electrodermal activity [8], heart rate variability [9] and brain activity [10] in the assessment of the workload of ATCOs. In particular, the techniques used in this study focused on measuring brain activity, specifically using electroencephalography (EEG) techniques.

EEG consists of the study of brain activity based on the differences in potentials recorded by a series of electrodes strategically placed in different regions of the scalp [11]. Although originally a complex and invasive procedure, used only in the field of medicine, these techniques have advanced significantly and are used in many different sectors and live situations. For example, in Ref. [12], the authors recorded EEG data from college aviation students in a real flight situation. Another interesting study [13] examined the effects of mental workload and time of day on various EEG parameters of professional air traffic controllers working in an area control centre (ACC) during their work on site.

EEG techniques have many advantages that justify their use. These include their capacity for continuous data recording, with high temporal resolution [14]. This makes these techniques suitable for use in critical sectors with variable task demands for front-line professionals. The aviation sector, in general, and air traffic control, in particular, fit perfectly into the above definition.

Many studies have used EEG data to establish interesting methodologies and models to improve the performance of aviation professionals. As an example, the authors of [15] proposed a method that could be applied to the development of intelligent warning systems to avoid fatigue. In their case, the input data were EEG data from commercial pilots. Another example of the use of EEG techniques related to aircraft pilots is Ref. [16]. This study proposed a convolutional neural network to classify EEG features as a function of different workload situations in a realistic simulation environment. Several studies using EEG techniques have also been published in the field of ATC. In Ref. [17], the authors presented a methodology that uses EEG measurements as a metric for comparison with the voice analysis of different ATCOs to conclude that voice parameters related to energy and stress correlate more strongly with changes in energy in different EEG frequency bands. The study presented in Ref. [18] also focuses on air traffic controllers. It showed that certain EEG characteristics, namely theta waves in the frontal and parietal zones and alpha waves in the frontal zone, were valid for use in analysing the cognitive behaviour of air traffic controllers.

EEG signals are usually analysed based on specific rhythms called frequency bands. These frequency bands are (from lowest to highest frequency) delta, theta, alpha, beta, and gamma waves. Depending on the cognitive situation the person is in, one type of band tends to dominate.

In adults, delta waves are associated with deep sleep. Theta waves are associated with drowsiness and sleep state. Alpha waves predominate during states of relaxation [19]. Beta waves tend to dominate during periods of concentration. Finally, the higher frequency waves, the gamma waves, appear in situations of language processing and memory [20]. The frequency band thresholds used in this study were the frequency band limits determined by EMOTIV, the manufacturer of the sensors used, as will be explained below. These limits are as follows. Theta waves cover frequencies from 4–8 Hz, alpha waves from 8–12 Hz, beta waves from 16–25 Hz, and finally gamma waves from 25–45 Hz.

1.1. Motivation of the Research

As shown, EEG techniques have been and are being used in a wide variety of studies in many different fields, including air traffic control.

As these techniques are of great importance, many equipment manufacturers and other software development companies offer complete programmes for the calculation of indicators and indices using EEG data. Although these tools are very powerful and enable researchers to obtain useful data and graphical representations, they have a number of limitations when it comes to interpreting some of the results.

- The definition of EEG parameters is often complex to understand when applied to real operational scenarios. This may not be a problem for an experienced EEG practitioner. However, if the aim is to extend the possibilities of this technology to professionals unfamiliar with the techniques, it is important that the interpretation of the parameters is clear and explainable.
- As much of this software is proprietary and the parameters are provided by different companies, the complete process of calculating and obtaining the parameters is unknown. This is a problem in terms of gaining knowledge of the models used or extending the analysis to situations other than the one in which the results were initially analysed.
- Some of these programmes have been developed for specific data acquisition equipment. In other words, compatibility problems may arise if two different companies' measurement equipment is used to collect data.

Considering all the above, the aim of this paper is to solve the above challenges and present a study in which the basic concepts are explained, software to obtain the parameters is developed, and the analysis techniques used are presented in detail. The aim is to make the work developed available to the widest possible audience and to demonstrate that it can be used in real air traffic control environments.

1.2. Objectives and Implications of the Study

Specifically, this work has four main objectives:

- Select a set of EEG parameters considered to be the most representative for use in the ATC domain. Most importantly, these parameters should be intuitive and explainable. It was also a requirement of this study that the calculation of these parameters was documented and that their application was sufficiently justified by their use in previous studies.
- Development of software to automatically obtain the selected EEG parameters. Software development was an essential step in the study. This idea was aimed at improving the readability and complete calculation process of the parameters.
- For this purpose, data specifically recorded for the study were used. These data were recorded using a real-time simulation (RTS) platform capable of reproducing a real operational scenario of the en-route phase of flight. The idea was to be able to study the behaviour of the parameters in a realistic situation but taking advantage of the possibilities of using a simulation platform, such as the design of the ATC events that occurred during the exercise.

- Finally, it was expected to draw conclusions on the behaviour of the parameters when studied against two variables that characterised the state of the sector during the simulation. These parameters were the taskload parameter based on ATC events and the number of simultaneous aircraft in the sector.

The following sections are structured to explain the process followed to achieve the four objectives mentioned above. Based on other models widely used in EEG studies, this paper proposes four main contributions:

(1) To propose a continuous working methodology, from the collection of experimental data to the calculation of parameters and the analysis of results. This makes it possible to improve the traceability of the process and the explainability of the parameters used.

(2) To present the stages of development of the software created and the criteria considered for the development of the analysis of the evolution of the parameters. It is expected that this process can be used in other research projects in aviation and other sectors.

(3) To make a proposal for the use of the six EEG parameters studied, excitement, stress, boredom, relaxation, engagement, and attention, in real operational scenarios, and to validate their application in a real-time simulation platform.

(4) In this study, particular attention has been paid to explaining the concepts of EEG as clearly as possible. While this may not be necessary for professionals with experience in the field, the aim is to bring the potential of these techniques to other aviation professionals who are not familiar with them and to present the great opportunities they offer in a clear and systematic way.

The remainder of the paper is structured as follows. Section 2. Materials and Methods presents the methodology of the study, the EEG sensors used, and the simulation campaign developed. Section 3 presents the variables used in the study. The independent variables were the taskload parameter based on ATC events and the number of simultaneous aircraft in the sector. On the other hand, the dependent variables were the six selected EEG parameters. Subsequently, Section 4 presents the software developed in MATLAB to calculate these EEG parameters from the raw data. Section 5 presents in detail the analysis of the behaviour of the EEG parameters and then the relationship between these parameters and the independent variables. Section 6. Discussion later presents the main findings obtained and highlights the applicability of the developed study in real air traffic control environments and some limitations of the results obtained that will be considered in future work. Finally, Section 7. Conclusions and Future Work summarises the main conclusions of the work and lists several avenues for future research.

2. Materials and Methods

This section presents, on the one hand, the methodology of the study and, on the other hand, the materials used. The materials are divided into three categories, including the simulation platform, the characteristics of the EEG equipment used to record the data, and some relevant details of the experimental procedure followed.

2.1. Methodology

Before explaining each of these stages in detail, it is necessary to mention some of the previous work that allowed this process to begin.

Prior to the start of the current research, the simulation platform used was configured for the development of experiments related to human performance, and various simulation campaigns were carried out to record neurophysiological data.

Additionally, there was previous experience in the analysis of EEG data, and work had been performed to analyse certain parameters provided by the headset manufacturer.

The methodology used in this study was divided into five stages. These stages are presented in the diagram in Figure 1.

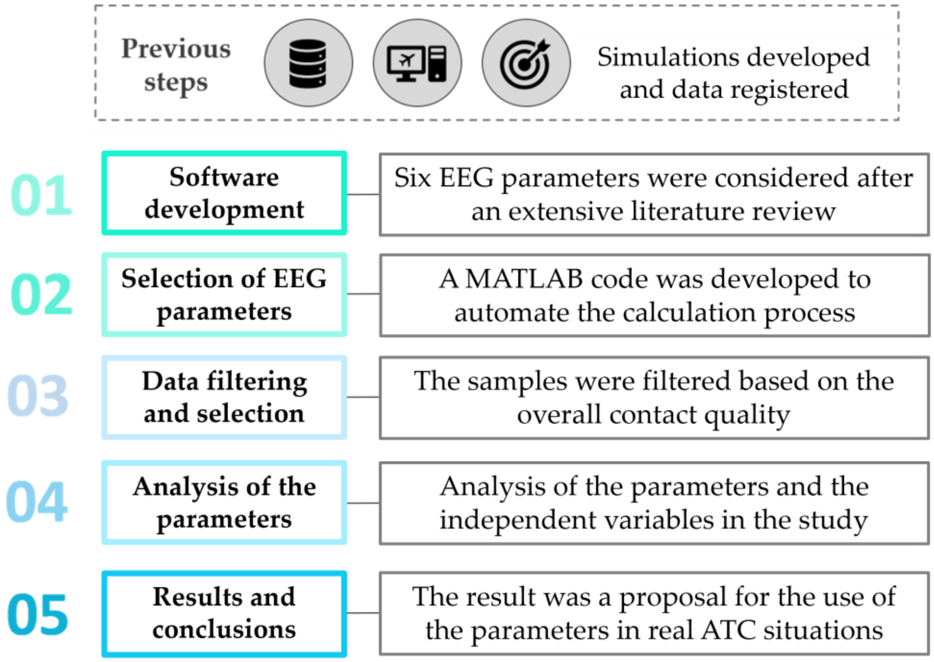

Figure 1. Stages of the methodology followed in the study: selection of EEG parameters, software development, data filtering and selection, analysis of the parameters, and results and conclusions.

The first stage of the methodology consisted of a detailed literature review to identify suitable EEG parameters. Three different aspects were considered in the parameter selection process:

1. These parameters have been used in other studies and their validity has been demonstrated in previous work.

2. The calculation process was reproducible so that they could be implemented using the software developed as part of the study.

3. The parameters were easy to interpret once defined.

Once the parameters had been selected, it was time to move on to the second stage of the methodology. This stage consisted of programming the software to automate the calculation of the parameters. As will be explained in later sections, the software was programmed in MATLAB. The software was developed in such a way that the user only needs to enter the data to be analysed and select the minutes of the recording where to start and end the analysis. Then, the software automatically calculates the six EEG parameters for the different minutes of the simulation.

The software included several customisable parameters, making it applicable to other experiments or other areas of application.

Once a database of all the parameters of all the participants had been obtained, it was necessary to carry out a filtering process to determine whether any of the samples should be discarded before continuing the study. To perform this filtering, the overall contact quality parameter was used.

After the previous step, it was time to proceed with the detailed analysis of the parameters of the selected samples. For this purpose, two complementary lines of work were followed:

1. First, an exploratory analysis of the EEG parameters and a series of graphical representations was carried out. The aim of this part was to identify trends and to draw first conclusions based on the graphical analysis.
2. Then, a numerical analysis was carried out between the EEG parameters and two variables chosen to characterise the situation of the sector during the development of the simulations. The use of linear regression techniques and the application of the ANOVA test were part of the numerical analysis. Linear regression techniques

were used to establish relationships between the independent variables, that is, the taskload parameter and the number of simultaneous aircraft in the sector, and the EEG parameters. Additionally, the ANOVA test was used to determine whether there were significant changes in any of the EEG parameters when there were changes in the independent variables. The ANOVA test is a widely used statistical test. Specifically, the one used in this study was repeated measures ANOVA. The null hypothesis of the test was that the mean of the groups considered was equal. In cases where the p-value obtained was less than 0.05, the null hypothesis could be rejected.

Finally, based on the results obtained, a series of conclusions were drawn. The most important of these was a proposal for the application of the six EEG parameters studied in a real ATC environment. In addition, some proposals have been made to continue this line of research and complete the analysis already developed in this study.

2.2. Simulation Platform and EEG Equipment

The simulation platform used in this study was a very realistic air traffic control platform. It used the SkySim simulator developed by SkySoft-ATM. It included two en-route air traffic control positions referred to as ATCO 1 and ATCO 2. Both positions simulated the exercise in parallel and could interact with each other. When the experiment was designed, the sectors assigned to each position were selected so that they were not adjacent, so that the fact that one participant could not take part in the simulation would not affect the rest of the data collection. These two positions are shown on the right-hand side of Figure 2.

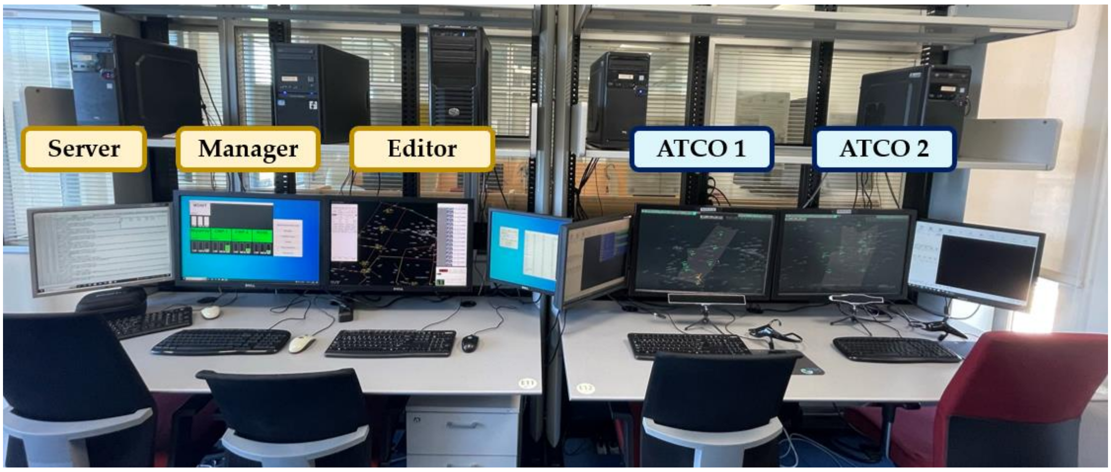

Figure 2. Simulation platform, including the data recording positions (server, manager, and editor) and the simulation positions (ATCO 1 and ATCO 2).

The simulation platform was completed by three additional positions used to manage the simulations. The first was the server, which was used to record the simulation data and configure the sectorisation assigned to the control positions. The second was the manager, which was used to manage the activation and deactivation of the other positions. The editor was the position used to design the exercises and then to start and stop the simulations. In the case of this position, special software called Radar Operation Simulator & Editor (ROSE), marketed by the company of the same name, was used. Additionally, to record the EEG data, each of the headsets worn by the participants had to be connected to a different computer for data recording. The EMOTIVPRO software was used for this purpose. The two computers used to record the EEG data were the server and the manager, as they were the least used once the simulation had started.

During the exercises, each participant wore a wireless headset to record EEG data. Specifically, the headset used was the EMOTIV Insight headset, a five-channel headset marketed by EMOTIV. This headset is shown on the left in Figure 3. The headset had five electrodes to record data. They were semi-dry electrodes. This makes it easier to fit, as only a few drops of contact liquid need to be placed on each electrode to improve contact quality before the headset is fitted.

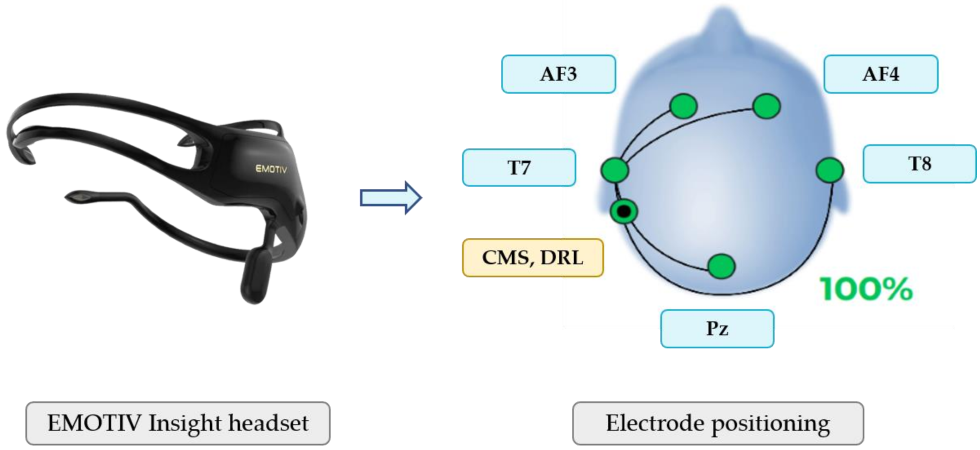

Figure 3. EEG equipment used in the study: EMOTIV Insight 5-channel headset (**left**) and electrode positioning on the scalp (**right**).

Electrodes were placed on the scalp using the international 10–20 system. This system is based on the identification of anatomical landmarks, such as the nasion, inion, and preauricular points [21]. Reference curves are defined from these points. The electrodes were placed at fixed distances that correspond to the 10% or 20% increase in these reference curves. The codification of electrodes changes depending on their position on the scalp. Their associated number increases as they move away from the centre. Odd numbers correspond to the left side of the brain and even numbers correspond to the right side [22]. When recording EEG data, there are two types of electrodes, active and reference electrodes. In this case, the active electrodes of the headset were located in the frontal area (AF3 and AF4), the temporal area (T7 and T8), and the parietal area (Pz). Their distribution on the scalp and the name of each electrode are shown on the right side of Figure 3.

In addition to the active electrodes, the Insight headset has two additional reference electrodes, both located on the left mastoid, known as CMS/DRL. The first, called the common mode sensor, is used as a reference for calculating the potential differences with the five active electrodes mentioned above. The second, called the common-mode cancelation sensor, serves as a noise cancelation electrode.

The right side of Figure 3 shows how EMOTIV visually indicates the contact quality of the electrodes. A colour code is used for this, ranging from grey for the worst contact quality to dark green, as shown in the figure, for the best contact quality. For data recording, the colour code is converted into a numerical code, from 0 for the worst contact quality to 4 for the best. The percentage represents the overall contact quality of the electrodes.

2.3. Experimental Procedure

After presenting the simulation platform and the EEG equipment used for data recording, this section describes the main aspects of the experiment developed. This includes relevant information regarding the exercises designed for the real-time simulations, the participants, and the EEG data recorded.

This experimental research was approved by the Ethics Committee for R&D + i Activities of the Universidad Politécnica de Madrid. Before developing the simulations, all participants were informed of the purpose of the experiment and that their data would be recorded and analysed. They all participated in the research on a voluntary basis.

2.3.1. Simulation Exercises

The exercises simulated in the experiment were all developed by the Universidad Politécnica de Madrid. A total of four different exercises were simulated, in which the task demand or taskload value was progressively increased. All exercises lasted 45 min. The participants visited the simulation platform twice to develop simulations with data collection. There was one week between the two sessions. In the first session, the participants simulated exercises 1 and 2 and in the second session exercises 3 and 4. There was a one-hour break between the simulation of the two exercises, during which the participants were allowed to take off the headset.

Before the data collection exercises, the participants received documentation on the basic commands of the simulator and completed an initial training session on the platform. During this session, they were able to practice the basic commands of the platform and perform short exercises, trying all the tools that they would later use in the data collection exercises.

During the simulation exercises, participants were free to implement the control actions they considered appropriate for the safe progress of the aircraft in the sector. The information available to them for each aircraft was a flight progress strip containing information on the route the aircraft was to follow and the flight levels associated with each waypoint. If the aircraft deviated from its original flight plan, it was the ATCO's responsibility to return the aircraft to its flight plan if possible and without causing a conflict.

The simulation platform had a conflict detection tool that alerted the ATCO whenever two aircraft were calculated to be within 7.9 NM of each other. A conflict was considered when the distance between aircraft was less than 5 NM. In terms of conflict resolution, the participants were free to implement the resolution in the way they considered the most optimal, but the platform did not propose any resolution suggestions.

2.3.2. Participants

A total of 16 participants took part in the experiment. For the sake of homogenisation, they all had common characteristics. They were all ATCO students with an average age of 21 years. All of them had normal or corrected-to-normal vision. Furthermore, they had all received the same theoretical and practical training. As part of this training, they were already familiar with the functioning of a control position, basic control actions, and conflict resolution strategies.

Their selection to participate in the experiment was based on their performance in various exercises and tests during their training. Although they had completed control exercises before, this experiment was their first contact with the SkySim platform. For this reason, training and familiarisation with the platform were conducted before data collection. The training was the same for all participants.

2.3.3. EEG Data Registered during the Simulations

During the development of the simulations, EMOTIVPRO software version 2.0 was used to record the EEG data. This software allowed the evolution of certain parameters to be monitored in real time. If there was a loss of connection or contact with one of the electrodes, discontinuities or interruptions in the recordings were visible. It also allowed data to be downloaded for further analysis in CSV format.

When the data were downloaded, a database of 84 different variables was available for each of the exercises. The following were the most relevant variables for this study and will be used in later sections of this paper to carry out the analysis of the EEG parameters.

- EEG variable.<sensor>. There was one such variable in the database for each of the five electrodes on the headset, where <sensor> is replaced by AF3, AF4, Pz, T7, and T8, respectively. This variable represents the value of the signal registered at each of the electrodes. It is the potential difference between each of the electrodes and the reference electrodes. The unit of measurement is μV. All values shown in this column had a 4170 μV increment applied by the manufacturer to the raw recorded signal. This variable was fundamental in the study, as it was the starting point for the calculation of the EEG parameters. A value of this variable was obtained for each recorded sample.

- CQ.Overall. This variable expresses the overall contact quality of the five electrodes. EMOTIVPRO uses the contact quality (CQ) variable as a measure of the impedance that characterises the quality of the electrical signal that passes through the sensors to the reference electrodes [23]. This variable takes values between 0 and 100, and a value was obtained for each sample recorded. In this study, it was used to filter the samples to select those with better contact quality.
- POW.<sensor>.<band>. This variable represents the power spectral density (PSD) value recorded on each of the electrodes for each of the corresponding frequency bands. In <band>, there are five frequency bands considered by the manufacturer. The first of these are the theta waves. The next band corresponds to alpha waves. The band associated with beta waves is divided into two: beta low (12–16 Hz) and beta high (16–25 Hz). Finally, the last band is gamma waves. In this study, the two bands associated with beta waves were combined and considered as a single frequency band, from 12 to 25 Hz. Regarding the values of this variable, in the database, a value was obtained every 15 samples, i.e., 8 PSD values were obtained in 1 s. In this study, the PSD was calculated from the raw data recorded by the headset. However, this value was used as a valid reference for comparison with the value obtained from the MATLAB software version 2022b programmed to calculate the parameters.

3. Variables Considered in the Study

This section presents the variables considered in the study. It is divided into two subsections. The first subsection presents the independent variables in the study. These variables were the taskload based on the task demand that the ATC events occurring in the simulation placed on the ATCO and the number of simultaneous aircraft in the sector per minute. The second subsection presents the EEG parameters calculated in the study. These subsections explain the interest of considering each of these variables, as well as the process followed for their calculation.

3.1. Independent Variables Considered in the Study

The independent variables of the study were used to characterise the situation of the ATC sector during the simulations. They were used as a reference to analyse the behaviour of the EEG parameters in response to changes in the situation of the sector. As this was a within-subject experiment, it was necessary to define a methodology to adequately define the evolution of these variables for each participant.

3.1.1. Taskload

In the study, the taskload parameter was considered to quantify the task demand imposed on the ATCO by the occurrence of specific ATC events during the simulation.

During the design of the exercises, a design taskload distribution profile was defined. In other words, certain ATC events were designed to occur at certain times during the simulation. The evolution of the design taskload followed a different pattern in each of the four exercises considered in the experiment.

However, since each participant was free to manage the aircraft within his or her sector, the actual taskload profile faced by each participant was different. The methodology developed based on previous simulations to obtain the taskload profile adapted to each participant can be found in a previous work by the authors [24].

In this section, only the most important aspects of this process will be mentioned to clearly illustrate how to obtain the taskload parameter, which will be used in later sections to study the evolution of the EEG parameters.

The taskload parameter was defined per minute during the simulation. To calculate this value per minute, a weighted sum of the ATC events occurring in that interval was performed. In total, nine ATC events were defined to model the main actions of the ATCO during the simulation. Each of these ATC events was characterised by a base taskload score and an average duration. The base score was determined prior to the development of the simulations, based on an expert assessment carried out with experienced ATM personnel and considering the opinion of active ATCOs. The average duration value was defined considering the way these ATC events were presented in the simulator and the actions taken by the participants to implement these events on the platform.

These ATC events are listed in Table 1. For each of them, the name, the average duration, and the associated base taskload score are presented.

Table 1. ATC events considered in the definition of the taskload parameter: name, duration, and base taskload score.

ATC Event	Duration [s]	Base Taskload Score
Aircraft identification	10	1
Aircraft takeover	30	3
Aircraft handover	30	3
Cruise–cruise conflict	30	7
Overtaking conflict	30	8
Vectoring	30	3
Change of flight level	10	3
Change of speed	10	3
Aircraft monitoring	60	0.1/aircraft

The ATC events considered were divided into four groups: routine ATC events, those modelling conflicts between aircraft, those related to the resolution of conflicts or discrepancies in aircraft flight plans, and monitoring.

The first three events shown in Table 1 are part of the routine events group. The first, aircraft identification, considered the fact that the ATCO detects that a new aircraft appears in the ATC sector. When identifying such an aircraft, the ATCO checks its flight plan and verifies that the conditions of entry into the sector match the conditions specified in the flight progress strip. Once this process has been completed, the aircraft shall be accepted. This process was modelled by the aircraft takeover event. Similarly, when the aircraft is about to leave the sector, the ATCO must check the flight progress strip again and ensure that the aircraft leaves the sector at the correct waypoint and flight level. All the above was modelled by the aircraft handover event.

The following two events were associated with aircraft conflicts. In general, two types of conflicts have been modelled, defined as situations where the separation between aircraft is less than 5 NM. The first was the cruise–cruise conflict, to denote that the conflict occurs between two aircraft that are established at cruise flight levels. The overtaking conflict event considered a special situation, where the two aircraft followed the same route. Initially, the aircraft were separated by a certain distance of more than 5 NM. However, subsequently, the second aircraft accelerates and starts to close the distance to the first aircraft, until the minimum separation is infringed.

The third group of ATC events was related to clearances to aircraft to modify their current state, either by changing the route (vectoring), changing the flight level, or changing the speed. These events may occur in response to a conflict situation between aircraft or due to the identification of a discrepancy between the flight plan that the aircraft should follow and its actual flight plan.

Finally, there was a last event related to the monitoring of aircraft to verify the implementation of the clearances and to monitor their evolution in the sector. In this case, unlike the previous events, the monitoring event was modelled per minute and was associated with each aircraft. In other words, it was assigned a taskload score of 0.1 for every minute an aircraft was in the sector.

One final consideration should be explained. After discussing the taskload scoring system with various ATCOs, their recommendation that the base taskload score should increase as the number of simultaneous aircraft in the sector increases, due to the increased difficulty of the actions, was considered. This was modelled by the traffic factor. This was implemented as follows. If the number of simultaneous aircraft in the sector is less than 5, the base taskload scores are applied. If the number of simultaneous aircraft is between 5 and 9, the medium traffic factor is applied, and the base taskload score of all absolute events (i.e., all except the monitoring event) is increased by 5%. If the number of simultaneous aircraft in the sector exceeds 10, the high traffic factor shall be applied, and the base taskload score of all absolute events shall be increased by 10%.

3.1.2. Number of Simultaneous Aircraft in the Sector

The modelling of the number of simultaneous aircraft was based on the identification of two ATC events that occurred in the simulations, the identification of an aircraft and the handover of an aircraft.

To obtain this parameter, an aircraft counter was programmed. Each time an aircraft appeared in the sector and the participant was aware of it, the counter was increased by one unit. Similarly, when an aircraft finished its evolution in the sector and the participant handed it over to the next sector, the counter subtracted one unit.

This parameter was expressed per minute. To define the number of simultaneous aircraft in the sector during a minute, a weighted sum was calculated based on the number of aircraft present at the corresponding time within that minute. In this way, aircraft entering or leaving the sector in the middle of this interval were included in the definition of the parameter.

3.2. Dependent Variables: EEG Parameters

After presenting the independent variables of the study, this subsection explains the dependent variables, i.e., the EEG parameters considered.

As stated in the methodology requirements, these parameters must have been used in previous studies and be calculated following a known procedure, as well as be explainable. In this subsection, it will be justified that the selected parameters meet the three requirements stated above.

The six parameters considered in the study were excitement, stress, boredom, relaxation, engagement, and attention. The first four were derived from the so-called arousal-valence model. The fifth was obtained using the engagement index formula, and the last one was obtained from the so-called R parameter of attention. All of them were calculated by considering variables associated with frequency bands.

There is a logic to the number of selected parameters. Prior to this research, the EEG parameters provided directly by the manufacturer of the headset using the EMOTIVPRO software were analysed. These were a total of six parameters known as performance metrics. They were defined as stress, engagement, interest, excitement, attention, and relaxation. Although these parameters are very useful, they have some limitations, especially when it comes to investigating how they are calculated. The algorithms used by the manufacturer are not known. For this reason, the present study attempted to select EEG parameters that were as close as possible to those provided by the headset manufacturer but following a known calculation process. As will be explained below, the four parameters selected for reference in the arousal-valence model were chosen for their similarity to the previously mentioned performance metrics. In addition, it was considered important to include two additional parameters due to their interest and use in previous studies.

Some of the finally selected parameters have previously been used in aviation studies. For example, the authors of Ref. [25] focused their study on the variation of arousal and affective valence parameters in relation to different tasks of variable difficulty during aviation training. In their case, the arousal values were calculated from electrodermal activity and the affective valence values from facial expressions. The study of the emotional state of pilots during the cruising phase of flight was the subject of Ref. [26]. Among the parameters used to characterise it were arousal and valence, determined from EEG and electrocardiogram techniques. Their results showed a relationship between these neurophysiological signals and pilots' emotions. In the field of air traffic control, the authors of Ref. [27] studied the influence of emotion and workload on the performance of participants in a simulated environment. One of the parameters used was arousal, based on skin conductance.

Throughout this section, reference is made to other studies when presenting the formulae used to calculate the EEG parameters. Although these parameters, or a combination of them, have been used in previous studies, to the best of the authors' knowledge, this is the first study in the field of ATC to use them all together and to explain the complete process followed in their analysis, from the recording of the raw data, through their calculation, to their detailed analysis.

3.2.1. EEG Parameters Derived from the Arousal-Valence Model

EEG techniques have been shown to be very useful in the automatic recognition of human emotions [28]. The arousal-valence model, also known as Russell's two-dimensional model [29], is currently the most widely used model to characterise emotions using EEG.

This model represents emotions in a two-dimensional space bounded by two scales, which can be compared to two axes of coordinates. The first of these, which corresponds to the X-axis, is valence. This parameter represents the pleasantness of the stimuli. Positive values on this scale would be associated with pleasant stimuli. On the contrary, negative values would be associated with unpleasant stimuli [30]. The second scale, which corresponds to the Y-axis of the graph, corresponds to arousal, which represents the degree of activation. Positive values of this parameter are associated with a state of arousal. On the contrary, negative values on this scale are associated with a state of deactivation.

The intersection of the valence and arousal axes defines a two-dimensional space in which the different emotions can be classified. A graphical representation based on Russell's model [29] is shown on the left side of Figure 4.

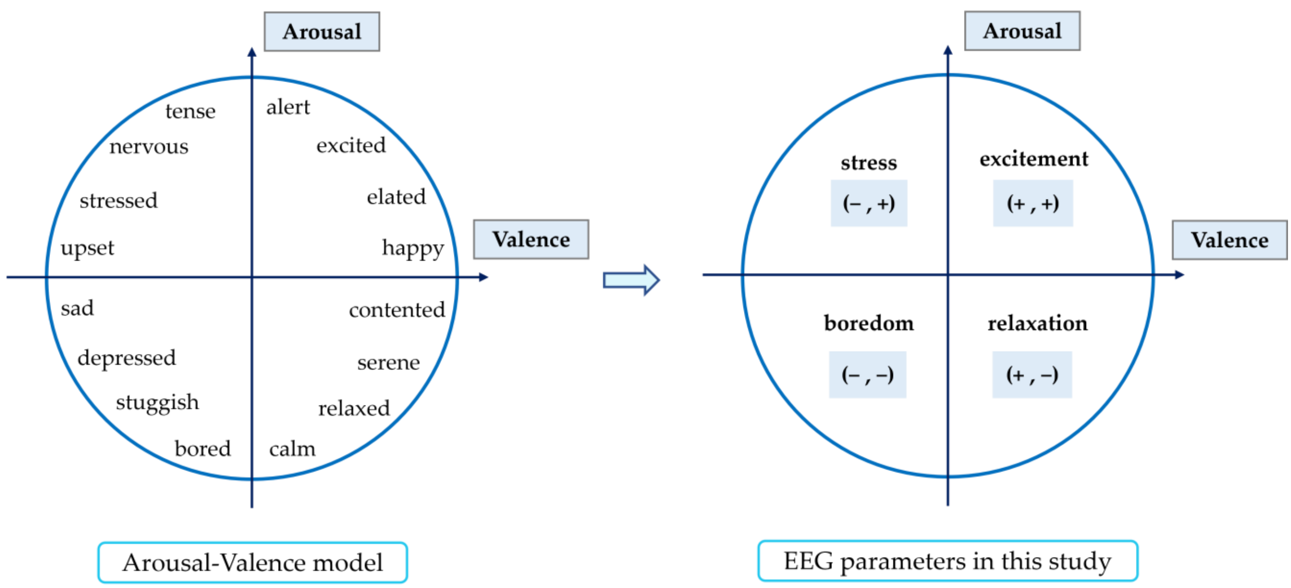

Figure 4. Arousal-valence model (**left**) and adaptation of the model to represent the EEG parameters considered in the study (**right**).

Based on this model, this study aimed to simplify it and consider four parameters, each representing one of the four quadrants into which the space is divided. Using valence as the X-axis and arousal as the Y-axis, the four EEG parameters considered counterclockwise from the quadrant where both values are positive were excitement, stress, boredom, and relaxation. That is, the parameters considered were:

- Excitement: it was considered representative of the quadrant where both valence and arousal are positive (+,+).

- Stress: it was considered as representative of the quadrant where the valence is negative and the arousal is positive (−,+).
- Boredom: it was considered representative of the quadrant where both valence and arousal are negative (−,−).
- Relaxation: it was considered as representative of the quadrant where valence is positive and arousal is negative (+,−).

A graphical representation of the parameters in the 2D space defined by the valence and arousal axes can be seen on the right-hand side of Figure 4.

Of the existing parameters in each of the quadrants in Russell's model, these four were considered as a reference because they were the most similar to some of the parameters provided by the EMOTIV headset for an initial analysis of the data. The aim was to compare these new metrics with those provided by EMOTIV and analyse their similarities.

So far, the qualitative definition of the first four parameters to be considered in the study as dependent variables has been presented. However, it is necessary to complement the above explanation with the analytical definition of the parameters to calculate them.

The first step was to define the formulae used to calculate the arousal and valence parameters. From the values of these two, the values of excitement, stress, boredom, and relaxation could then be calculated.

The formula used to calculate arousal appears in Equation (1) and has been defined based on the formula used in Ref. [31]. This study also used EEG data and an adaptation of the arousal-valence model. In that case, the reference emotions were happiness, anger, sadness, and relaxation.

ESD refers to the energy spectral density associated with the corresponding frequency band recorded at the indicated electrodes. The way in which the different values were obtained will be explained in the following section, which is dedicated to the software for calculating the parameters programmed in MATLAB.

$$Arousal = \frac{\Delta ESD_{\beta}(AF3) + \Delta ESD_{\beta}(AF4)}{\Delta ESD_{\alpha}(AF3) + \Delta ESD_{\alpha}(AF4)} \quad (1)$$

Equation (2) presents the formula used to calculate the valence parameter. This formula was adapted from the one presented in Ref. [32]. In this study, an interesting assessment of the emotional state of a series of workers was carried out while they were in situ at their workplace. Furthermore, the EEG device that they used for their measurements was also marketed by EMOTIV, but it had a larger number of electrodes than the headset used in this study. Therefore, it was necessary to adapt the formula to the number of electrodes of the EMOTIV Insight headset.

$$Valence = \frac{\Delta ESD_{\alpha}(AF4)}{\Delta ESD_{\beta}(AF4)} - \frac{\Delta ESD_{\alpha}(AF3)}{\Delta ESD_{\beta}(AF3)} \quad (2)$$

This parameter shows the difference between the brain waves recorded on the frontal right side of the brain ($AF4$) and the frontal left side ($AF3$).

3.2.2. EEG Engagement Parameter

The fifth parameter used in the study was engagement. The formula for the engagement index can be seen in Equation (3). As an example, this formula was used in Ref. [33], where the state of immersion of several participants in the performance of an experiment was studied. Specifically, the activity they were performing was playing a game. The study used this and other parameters to distinguish, based on EEG data, the occurrence of high-intensity events in the game from the normal state. In the above-mentioned study, EMOTIV equipment was also used for data recording.

$$Engagement = \frac{ESD_{\beta}}{ESD_{\alpha} + ESD_{\theta}} \quad (3)$$

For each electrode for which the parameter was to be obtained, this equation was applied. The use of this formula to calculate engagement involved the calculation of a new value as a preliminary step to the use of the formula. This was the *ESD* value associated with theta brain waves. Its calculation was also part of the MATLAB software developed.

3.2.3. EEG Attention Parameter

The final EEG parameter used in this study was attention, which can be calculated using the formula given in Equation (4). As in the previous equation, Equation (4) should be applied for each electrode for which the parameter was to be obtained.

$$Attention = \frac{ESD_{\alpha}}{ESD_{\beta}} \quad (4)$$

This parameter calculates the ratio between the alpha waves, associated with a relaxed state, and the beta waves, associated with an active brain state. Therefore, the lower the parameter, the higher the value of beta waves and the higher the brain activity [34]. This equation was used in the study mentioned in the previous reference, which focused on the evaluation of different types of stimuli in the drowsiness experienced by drivers.

The four equations shown above allowed for the calculation of the arousal, valence, engagement, and attention parameters. The following section shows the process followed for the calculation of the six EEG parameters considered in the present study.

4. From Raw Data to EEG Parameters: Software Development

As part of the study, a MATLAB code was developed to automate the process of calculating the EEG parameters. This section presents the advantages of this software and the process followed by the code to calculate the parameters. It also presents some values and parameters that can be adapted by the user to extend the application of this code and to use it in different experiments.

4.1. Advantages of the Code Developed

When it was decided to automate the process of calculating the parameters, several options were considered. Finally, it was decided to use MATLAB version 2022b because of its ability to work in the frequency domain.

One of its toolboxes, called the Signal Analyser, includes a very interesting function for this application. This is the spectrogram function that allows the PSD of the signals to be calculated. For the software to work correctly, it is necessary to have downloaded this toolbox in advance. Some of the main advantages of the software developed are as follows.

- The software is easy to use. It has been designed in such a way that the user only needs to enter three input data when the code starts running: the number of files to be analysed, the start time, and the end time of the analysis. The software then runs until a matrix of EEG parameters for the duration specified by the user is obtained.
- The software allows several exercises to be analysed simultaneously. In this way, all the EEG parameters of the files entered by the user can be calculated at the same time. This speeds up the process of obtaining the parameters.
- All the exercises simulated in this study lasted 45 min. However, it may be of interest to limit the analysis time to only some minutes of the simulation. The software has been designed to allow the user to set these parameters when the software starts running. Conditionals have been defined in the following steps so that the code can consider the different possibilities of start and end time of the analysis process.
- At a more detailed programming level, certain parameters have been established in some of the stages adapted to the study. For example, the grouping values of the parameters. However, these values can be easily modified for use of the code in other applications and experiments. This enhances the versatility of the code.

- Taking all this into account, it has been possible to develop a code that automates the calculation of the parameters. It has been divided into logical stages that allow its application to be extended to other experiments and scenarios by modifying some parameters.

4.2. Calculation of EEG Parameters

This subsection presents the process followed by the software for calculating the EEG parameters from the input data entered by the user. The process was divided into a total of nine steps. The purpose of each of them will be briefly explained, and certain values that can be modified in future applications of the code will be indicated.

Figure 5 shows schematically the process used to calculate the parameters, with the nine stages presented in chronological order.

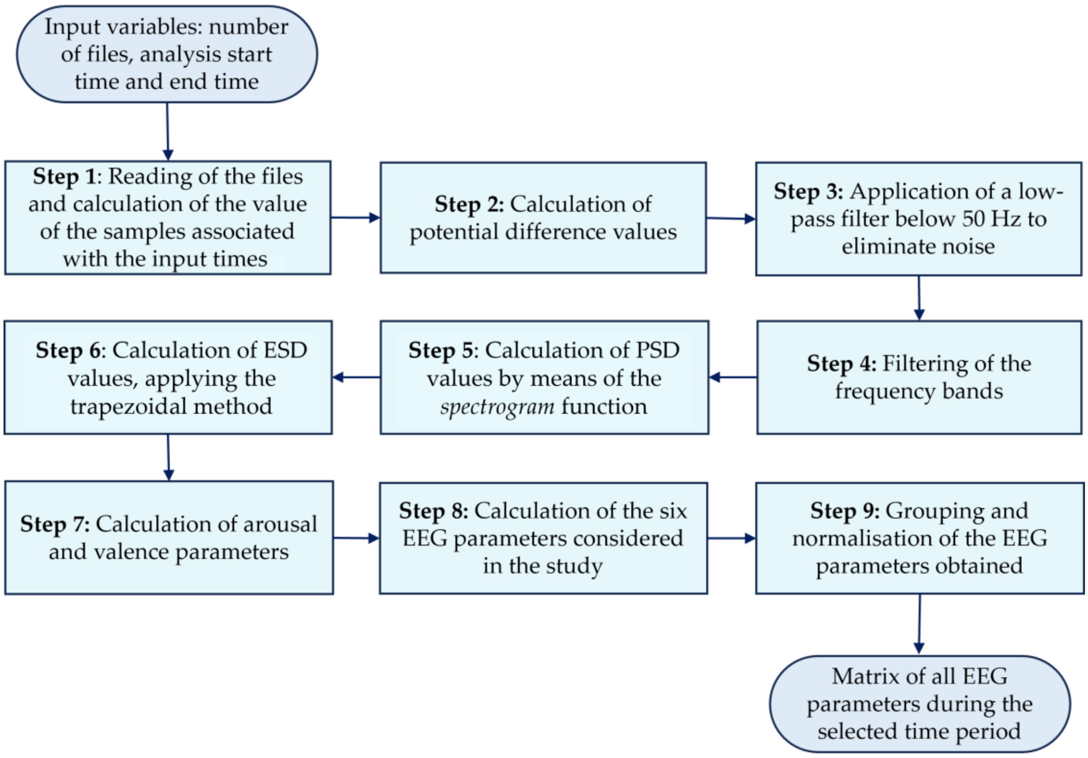

Figure 5. Steps followed in the process of parameter calculation using MATLAB: from the input variables by the user to the definition of a matrix with all EEG parameters during the selected time period during the simulation.

When the programme is first run, the user is asked to enter three variables as input data:

- The first is the number of files to be analysed. The files to be analysed by the software must be Excel spreadsheets. The user should enter the name of each file. The software will prompt the user to continue entering files until the total number of files defined is reached.
- The second parameter represents the minute of the simulation at which the analysis is to be started. The user can choose to start the analysis at the beginning of the recording or later.
- The third is the last minute of the simulation to be included in the analysis. The user can choose to analyse the recording to the end or to stop the analysis earlier.

With these values entered, the software begins to execute the various lines of code. The first step is to convert the times entered by the user into the corresponding sample number. To do this, the time in minutes entered by the user is multiplied by 60 to obtain the time in seconds and by 128, the sampling frequency of the headset, i.e., the number of samples per second that it records. At this stage, the software also reads the data entered by the user and stores them in a matrix.

The second step consists of calculating the raw potential differences, that is, the potential difference between the active electrodes and the reference electrodes recorded by the headset. As a preliminary step, the software calculates a series of variables to adapt the process to the start and end time values of the analysis entered by the user. To do this, some conditionals were defined. Depending on the parameters entered by the user, the software will start the analysis at the beginning of the recording or at the sample corresponding to the starting minute entered by the user. The same applies to the end of the analysis. The analysis will end at the end of the recording if the user has specified this minute as the end time. If the user prefers to stop the analysis earlier, the software will cover the analysis up to the sample corresponding to the last minute entered.

Whatever the situation, this stage of the software allows the obtention of the actual potential differences recorded by the headset. By default, EMOTIV adds a value of 4170 µV to the recorded values to make them easier to display. At this stage, the code reads the raw data recorded on each of the electrodes and subtracts this difference. At the end of the execution of this code fragment, for each of the exercises, there are five column vectors (each corresponding to an electrode), with the actual value of the signal in microvolts.

The third stage consists of applying a filter to remove noise or interferences from the signals. Most EEG signals lie between 0.5 and 50 Hz. Values above this threshold are usually associated with artefacts and other noise and should be removed from the analysis [35]. To do this, using the MATLAB butterworth function, a low-pass filter was applied at 50 Hz. This filter is used to remove frequencies above this value. The frequency bands of the brainwaves are all below this threshold.

The fourth step is to filter the frequency bands. To do this, it was necessary to apply different filters to each of the electrodes considered in the study to obtain their corresponding frequency bands. As explained in Section 1. Introduction, bandpass filters were applied with the wave thresholds considered by EMOTIV. That is, between 4 and 8 Hz for theta waves, between 8 and 12 Hz for alpha waves, between 12 and 25 Hz for beta waves, and between 25 and 45 Hz for gamma waves.

The next step is fundamental to the process. As discussed, when calculating the parameters, it is necessary to calculate the ESD values. However, as a previous step, the PSD values need to be calculated. PSD expresses the activity level in each frequency band considered in the study [36]. MATLAB has a very interesting function for this. This is the spectrogram function that allows the Fourier transform of the signal to be calculated. In addition, one of the variables calculated by this function is the PSD itself.

Two scalar numbers are required as input values to the spectrogram function. The first corresponds to the number of samples in each segment into which the signal is divided, and the second corresponds to the number of samples that overlap to obtain a value of the signal. In the case of the PSD values provided by EMOTIV, one value was obtained every 15 samples. For compatibility reasons, 256 and 240 were chosen as the corresponding scalar inputs for the spectrogram function. The code can be adapted to other applications by changing these two values. For the calculation of the parameters, it was necessary to use the data from electrodes AF3, AF4, and Pz. Therefore, the spectrogram function was applied to each of them to calculate the corresponding PSD values.

The next step is to calculate the ESD values. To calculate them, it is necessary to integrate the previously obtained PSD values. Different methods can be used to perform this integration. In this study, the trapezoidal method was used using the trpz function in MATLAB. To use this function, it was necessary to define the variables X and Y so that the MATLAB function calculates the integral of Y with respect to X using the trapezoidal method. In this case, X represented the frequency interval, while Y represented the PSD value [37]. After the application of this method, the ESD values for each of the electrodes could be obtained for each frequency band. In addition, to calculate the arousal and valence parameters, it was necessary to calculate the change in ESD between one value and the previous one. This is performed at this code fragment.

The next step was to calculate the values of arousal and valence, from which the four EEG parameters associated with Russell's model are obtained. This is performed by applying Equations (1) and (2).

Once these two parameters have been obtained as an intermediate step, the next step is to calculate the six EEG parameters.

- A series of conditionals were applied to obtain the parameters derived from the Russell's model. If the sign conditions were satisfied for each of the parameters shown in Figure 4, the corresponding module of the vector was calculated. If the condition was not met, the absence of such a value was recorded as 'NaN', equivalent to an empty cell, so as not to interfere with subsequent operations.
- To calculate the engagement parameter, Equation (3) was applied to sensors AF3, AF4, and Pz. The mean engagement value was calculated as the average of these values.
- To calculate attention, Equation (4) was applied to each of the sensors located in the frontal area of the brain and the average value was calculated.

The final step was to group and normalise the parameters. At this point, it was necessary to group the parameters according to the number of values per minute to be obtained. In this case, since the two independent variables of the study, i.e., taskload and simultaneous number of aircraft, were obtained per minute, it was of interest to obtain a value of the EEG parameters every minute.

The ESD values are not the same length as the original signals because different windows have been used. After calculation, eight ESD values per second were obtained. Therefore, to apply the loops at this stage for the grouping of the parameters, the step was 480, considering that 8 ESD values were obtained per second, and it was of interest to obtain a parameter every 60 s. This value can be modified if it is needed to change the frequency at which the parameters are obtained. Once the parameters have been grouped, they are normalised.

The last step is to save the calculated parameters so that they can be exported. This is performed by creating a matrix for each exercise. The calculated EEG parameters are stored in columns. One datum per minute is available at the interval specified by the user.

Finally, when the process is complete, the user must specify the name under which he/she wishes to export the parameter matrix. By default, it is saved as a plain text file. If the user wishes to export it as a spreadsheet, it is necessary to specify the extension when saving the file.

The result is a file containing all EEG parameters associated with an exercise, with the extension specified by the user.

5. Analysis and Results

After presenting the process followed to calculate the EEG parameters, this section describes their analysis. It is divided into three subsections. The first explains the filtering process carried out to include samples with the best contact quality in the study. This is followed by the results of the first stage of analysis, in which an exploratory data analysis of the EEG parameters was carried out and their evolution was graphically analysed. The section ends with the presentation of the results of the numerical analysis, which assessed the relationships between the independent variables of the study to the dependent ones.

5.1. Data Filtering and Sample Selection

As explained in the previous sections, the process of defining and calculating the parameters was very detailed. Furthermore, it was considered necessary to filter the samples prior to starting the analysis. For this purpose, it was considered that the most interesting variable among those provided by the headset software was the contact quality of the electrodes. There is a variable that represents the contact quality of all electrodes, called CQ.Overall. This variable was introduced in Section 2.3.3. Furthermore, there are equivalent variables to assess the contact quality of each of the headset electrodes.

In general, a sample was considered of good quality if the CQ.Overall value was above 50% for more than half of the recording and also if it was above 33% for more than two-thirds of the recording time. If only one of the above two conditions was met, the contact quality of the sensors used in the study was examined. If the individual sensors met their respective contact quality criteria, the recording was included in the study. If not, it was discarded.

The initial sample consisted of 63 recordings, as 15 participants simulated 4 exercises, while 1 participant simulated 3, as he was unable to complete the last session. After applying the sample selection criteria described above, a total of 50 exercises were included in the study.

All participants were included in the study, and it was not necessary to discard any of them due to general contact quality problems.

Once the filtering process was completed, a very large number of EEG samples could still be analysed. The results presented in the following subsections are the result of the analysis of these 50 samples with the best contact quality.

5.2. Exploratory Data Analysis and Graphical Analysis

The first step in this process was to obtain a general characterisation of the calculated EEG parameters. To do this, their descriptive statistics were calculated for each of the exercises, using values such as mean, standard deviation, or quartiles.

Once the statistical parameters were known, the graphical analysis of the EEG parameters began. The graphs shown as examples in this subsection correspond to data from Participant 2. This participant was chosen as an example because he was the first whose four exercises met the established filtering criteria and were included in the study.

Subsequently, graphs showing the evolution of the EEG parameters over time were generated. An example of the evolution of the excitement parameter over the course of Exercise 3 is shown in the left part of Figure 6. The aim of these plots was to graphically analyse the evolution of the parameters and to try to identify possible errors in their calculation (for example, if any of them were constant). Another aim was to analyse whether any of the parameters showed a very similar pattern of evolution. If this had been identified, a more detailed analysis would have been necessary to discuss whether it was of interest to consider both parameters in the study or only one of them. In this section, only a few examples will be shown to illustrate the graphical representations that were analysed. However, the volume of graphs analysed was very large. For example, for the parameter evolution graphs, one was obtained for each of the six EEG parameters. This means that six graphs were obtained for each exercise. As mentioned above, a total of 50 exercises were analysed, resulting in a total of 300 graphs of this type.

As part of the process, it was also interesting to create scatter plots that relate the values of the EEG parameters to those of the taskload. This was performed to analyse the dispersion of the values and to try to assess whether the registered data were correct and followed the typical pattern of an experiment. Many graphs of this type were represented. First, all the participants were combined, and the parameter values were plotted on the Y-axis and the taskload values on the X-axis. An example of this type of plot for the excitement parameter and Exercise 3 is shown on the right-hand side of Figure 6. Each participant is shown in a different colour. Dots of the same colour refer to data from the same participant. The graphs were then repeated, but with the data presented as the change in taskload from one minute to the previous one on the X-axis and the changes in the EEG parameter on the Y-axis. The analysis of these graphs showed that the dispersion of the data followed the pattern of the data registered in an experiment.

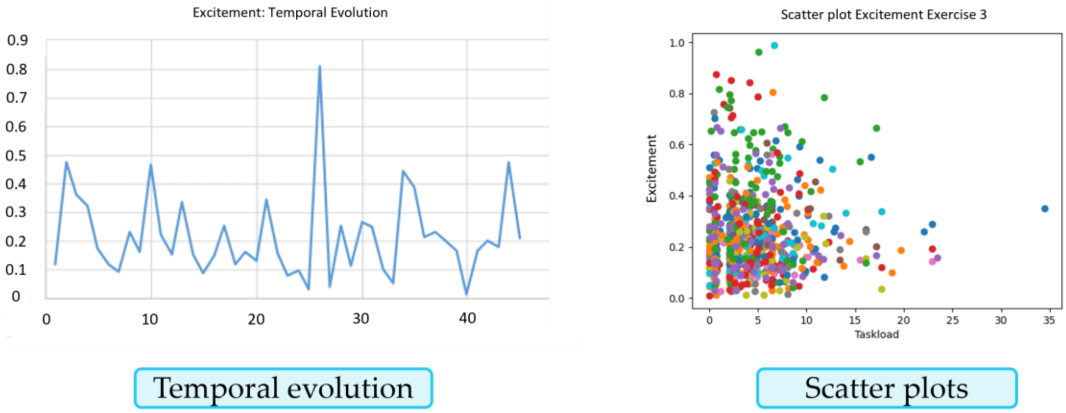

Figure 6. Examples of some of the representations used in the graphical analysis of the parameters: temporal evolution of the excitement parameter during Exercise 3 (**left**) and scatter plot of the excitement parameter versus taskload for the same Exercise 3 (**right**). The data for each of the participants in the study is shown in a different colour in the graph.

Another type of graph to be analysed in this part of the study consisted of a joint temporal evolution of each EEG parameter and the taskload. Although these relationships will be explored in more detail in the numerical analysis subsection, it was considered of interest to create a first visual representation of them. An example of this plot for Exercise 3 can be seen in the left part of Figure 7. In this case, the X-axis represents time and the Y-axis represents the change in the two parameters, i.e., the difference between their value in one minute and the previous minute. The taskload is shown in orange and the excitement parameter in blue. To be able to compare the two evolutions, it was necessary to apply a scaling to the taskload values to present them on the same scale as the parameter, which varies between 0 and 1.

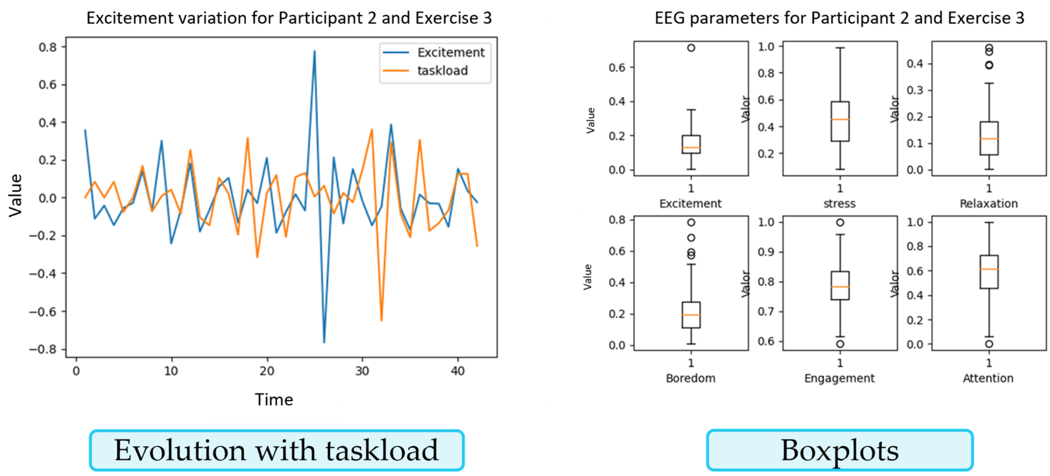

Figure 7. Graphical analysis of the evolution of the parameters: Evolution of the change in the excitement parameter in parallel with the change in the taskload (**left**) and analysis of the outliers of the EEG parameters using boxplots (**right**). Both plots are based on the data of Participant 2 and Exercise 3.

A very important step in the graphical analysis was to examine the outliers of the EEG parameters. For this purpose, boxplots of the six parameters obtained for each of the exercises were created. The boxplot for Participant 2 and Exercise 3 is shown on the right-hand side of Figure 7. In general, it was concluded that the EEG parameters showed either no outliers or very few. The next decision to be made was how to deal with these outliers. In general, in the case of EEG measurements, an outlier can occur under two circumstances:

- If there is an error in the recording of the data or a problem with the headset connection.
- Due to a sudden change in the situation of the sector during the simulation, resulting in a change in the recorded parameters.

The aim of the pre-processing stage was to eliminate as far as possible the outliers associated with the first case. To identify to which category the outliers belonged, a detailed analysis was carried out, trying to establish correlations between the moments in the simulation when these outliers were detected and the ATC events occurring in the sector at that time. It was concluded that most of the outliers occurred at times when ATC events occurred that significantly increased the task demand, e.g., multiple simultaneous conflicts. It was therefore concluded that these recorded values were related to the situation of the sector during the simulations, and it was decided to include them in the study.

After analysing all the graphs presented, three main conclusions of interest were drawn:

- Each of the EEG parameters showed different evolution patterns, which justified their inclusion in the study.
- It was possible to define a first graphical relationship between the evolution of the EEG parameters and the evolution of the taskload, which justified the development of a detailed numerical analysis to establish numerical correlations.
- Regarding the analysis of outliers, based on the boxplots created, it has been concluded that the EEG parameters presented no or very few outliers. Furthermore, relationships have been established between the recording of these outliers at times when there are important changes in the sector situation during the simulation. For this reason, these values were retained as part of the sample for further numerical analysis.

These conclusions were considered in the next stage, which consists of the numerical analysis between these EEG parameters and the taskload and number of simultaneous aircraft variables.

5.3. Numerical Analysis

As the final stage of the analysis of the EEG parameters, and considering the conclusions of the graphical analysis, a numerical analysis was developed. As explained in Section 2. Materials and Methods, this numerical analysis consisted of the application of linear regressions and the ANOVA test. On the one hand, linear regressions were used to establish relationships between the independent variables and the EEG parameters. In addition, the ANOVA test was used to determine whether there were significant changes in any of the EEG parameters with changes in the independent variables.

The following cases were studied using the two techniques mentioned above:

- Raw values of parameters versus taskload.
- Change in EEG parameters versus change in taskload.
- Raw values of the EEG parameters versus the number of simultaneous aircraft in the sector.

This subsection presents the process followed considering the above options. As an example of the results, those related to the number of simultaneous aircraft and the raw values of the EEG parameters will be presented. The results obtained in this case are representative of the rest. Although only the results of this case are presented numerically, the main conclusions drawn from the analysis of the other cases are also mentioned.

5.3.1. Linear Regressions

Regressions and linear correlations are widely used techniques. In this case, they are used to establish a relationship between the dependent variables, i.e., the EEG parameters, and the two independent variables. The relationship is quantified using the Pearson correlation coefficient. This parameter takes values between -1 and 1. After calculating the correlations, tables were created showing the Pearson correlation coefficient between the parameters studied for each participant and each exercise.

Before studying the three cases explained above, it was necessary to scale the taskload so that its values and the EEG parameters were on the same scale. The hyperbolic tangent method was used.

The first case study consisted of analysing the raw values of EEG parameters versus taskload. The best results of the Pearson correlation coefficient were obtained for the attention and engagement parameters.

The second case study consisted of repeating the analysis but considering the changes in both parameters. This means that, for both the taskload and the EEG parameters, the difference between the parameter value of one minute and the previous minute was calculated. The correlations obtained in this case are lower than in the first case studied. However, the best Pearson correlation coefficients were also obtained for the engagement and attention parameters.

In the third case study, the raw values of the EEG parameters were analysed against the number of simultaneous aircraft in the sector. Again, the highest correlation values were obtained for the engagement and attention parameters. Figure 8 shows the correlation coefficients obtained in this case.

Engagement vs. aircraft

	EXERCISE			
PARTICPANT	1	2	3	4
1			0.435233279	0.652958326
2	0.393805718	0.337911588	0.639963386	0.253859546
3	0.112371335	0.100192832	0.066259375	0.462421426
4		0.273743866	0.78704609	0.514893664
5			0.49109908	0.394300746
6		0.311449404	0.173477126	−0.021966634
7	0.626925856	0.158351602	0.075122293	0.381906347
8	0.224150249	0.484352197		0.664397553
9	−0.158945004		−0.221111326	0.026238907
10	0.080929326	−0.249483146	0.393015859	0.224505778
11	0.427778957	0.491747998	0.054883816	
12	0.400058029		−0.175659232	
13	0.645809738		0.523060708	0.436244962
14	0.042679208	0.417980868	0.582130253	0.198190758
15	0.394900225		0.433670828	0.415837126
16	0.501324568	0.580518396	0.545546531	

Attention vs. aircraft

	EXERCISE			
PARTICPANT	1	2	3	4
1			−0.243987875	−0.421023378
2	−0.405600318	−0.309597819	−0.599770692	−0.17137636
3	−0.362335501	−0.385123273	−0.620022423	−0.632255809
4		−0.263632853	−0.469859739	−0.058225455
5			−0.220628005	−0.296853507
6		0.168995431	−0.166991956	−0.139791912
7	−0.451147824	−0.311571688	0.288562548	−0.079286719
8	−0.28585607	−0.541949124		−0.620205996
9	0.453325619		−0.145797027	0.27618143
10	0.052161366	0.086005465	−0.453134963	0.074987651
11	−0.493807262	−0.337215423	−0.436508366	
12	−0.439991123		−0.202056432	
13	−0.480956647		−0.522353332	−0.39921076
14	0.094081213	−0.489413009	−0.592084405	−0.320760037
15	−0.395134831		−0.434539806	−0.205951108
16	−0.599209881	−0.585465442	−0.116303895	

Figure 8. Results of linear regressions of engagement (**left**) and attention (**right**) when analysed against the number of simultaneous aircraft in the sector. The colour of the cells varies according to the results of the correlation coefficient. White cells are below 0.2. Yellow cells are between 0.2 and 0.4. Results above 0.4 are green.

The rows of the table show the values obtained for each of the participants. The columns show the different exercises. Therefore, each cell represents the correlation coefficient obtained for a participant and a specific exercise. The grey-shaded cells correspond to the exercises that were not included in the study after the filtering process. The coloured cells show the results of the correlation coefficient. The white cells have a correlation coefficient of less than 0.2. The yellow cells have a coefficient between 0.2 and 0.4. The green cells have a correlation coefficient greater than 0.4. Moreover, as can be seen from the signs of the coefficients, in the case of engagement, most of the coefficients have a positive sign, while in the case of attention, most of them have a negative sign.

In general, it can be concluded that in the three cases studied, the best correlation coefficient values were obtained for engagement and attention parameters. Specifically, of the three cases studied, the best values were obtained when analysing the raw data from the EEG parameters versus the number of simultaneous aircraft in the sector.

5.3.2. ANOVA Test

Repeated measures ANOVA was used in this study. The results obtained with this test are easy to explain based on its hypotheses. Traditionally, the application of this test has required that the data follow a normal distribution. However, recent studies have concluded that the ANOVA test is robust to non-normality of the data under certain conditions. These include that the data samples are of the same or very similar size (a condition that is met in this study). Some studies have gone a step further and performed various simulations to analyse the effect of non-normal data on the validity of the ANOVA test. For example, in Ref. [38] the authors perform a large number of Monte Carlo simulations to conclude that the ANOVA test is robust to non-normality in the cases studied. Based on these references, this test was used in the study.

The first case to which the ANOVA test was applied was the EEG parameters and the taskload expressed as raw values. The steps followed to apply the test were as follows.

1. Three different groups were defined according to the taskload value. In the first group, the taskload value is less than 2.5. In the second group, the taskload value is between 2.5 and 5. In the third group, the taskload value is greater than 5.

2. Groups were created for all participants and exercises. In this study, Python programming language was used for the application of the test.

3. The mean of each group was calculated for each participant and exercise, and these values were stored in a dataframe.

4. The ANOVA test was applied. In cases where the p-value obtained was less than 0.05, the null hypothesis could be rejected. As discussed in Section 2. Materials and Methods, the null hypothesis of the test is that the mean of the three groups is equal.

In the case of application with the raw values of the taskload, statistically significant results were obtained for engagement and attention. These results complemented those already obtained in the case of linear regressions. These results showed that, for these two parameters, changes in their value were observed when the value of the taskload changed within the defined thresholds.

The second case study consisted of applying the test to the change in both EEG parameters and taskload from one minute to the previous one. The process followed was the same as in the previous case, except that in this case only two groups were considered. The first group corresponded to positive changes in the taskload parameter, and the second to negative changes. The results obtained were analogous to those of the previous case, with statistically significant p-values obtained for the engagement and attention parameters.

Finally, the last case study applied the test to the EEG parameters, but with respect to the number of simultaneous aircraft in the sector. The calculation process followed was the same as in the previous two cases.

In this case, three groups were considered for the application of the test. In the first group, the number of simultaneous aircraft in the sector was less than or equal to three. In the second case, it was greater than three but less than or equal to six. Finally, in the third group, the number of simultaneous aircraft in the sector was greater than six. The p-values obtained by applying the ANOVA test to this case are shown in Table 2.

Table 2. ANOVA test results (p-value) when applied to the case study of EEG parameters and the number of simultaneous aircraft in the sector.

EEG Parameter	p-Value
Attention	0
Boredom	0.4089
Excitement	0.6276
Engagement	0
Stress	0.0998
Relaxation	0.3761

As can be seen, the results were very similar to those in the case of the application of the test to the taskload data. The two parameters where the *p*-values were statistically significant were engagement and attention. As a particular feature of this case, the *p*-value associated with the stress parameter had a very low value but still did not meet the threshold criterion.

Applying the ANOVA test in the study complemented the results obtained when calculating the correlations, and statistically significant *p*-values were obtained for engagement and attention in all the cases studied.

6. Discussion

This section discusses and analyses the results obtained. It also highlights the potential practical applications of these results and points out certain limitations to the generalisation of the results obtained.

6.1. Results Discussion

First, the graphical analysis carried out led to several interesting conclusions. The first is that no patterns of similar evolution were identified between the parameters, which justified the inclusion of all of them in the study.

It has also been found that the dispersion of the data was typical of that expected from data recorded during an experiment.

The relationships between the changes in the EEG parameters and the taskload were graphically analysed. The conclusion was that they were interesting enough to be the subject of further numerical analysis.

Finally, after performing the outlier analysis, it was concluded that the EEG parameters had no or very few outliers. It was also concluded that these values occurred at times during the exercise when the ATCO's task demands changed, so they were retained as part of the study data.

After developing the numerical analysis between the values of the EEG parameters and the independent variables of the study, interesting results have also been obtained.

The first of these is that engagement and attention are the main parameters for which a relationship has been observed with both taskload and number of simultaneous aircraft in the sector.

This has been concluded in the case of linear correlations and is confirmed by the application of the ANOVA test. In the case of the correlations, these parameters are the ones for which a higher Pearson correlation coefficient was obtained. Furthermore, they were the only ones that were below the *p*-value threshold of 0.05 to obtain statistically significant results in the ANOVA test. The interpretation of these results is that, if there is a change in the value of the taskload or in the number of simultaneous aircraft in the sector, the engagement and attention parameters also change.

The fact that the same results were not obtained for the other four parameters does not imply that there is no relationship between these EEG parameters and the independent variables. In fact, in the graphical analysis of the changes in the parameters, similar behavioural trends of the taskload and these EEG parameters could be identified. The problem is that in many cases, these similar trends were out of phase over time. To obtain better results in the numerical analysis of these values, it is concluded that it may be necessary to identify this time lag and analyse it.

6.2. Practical Application of the Results

The results showed the interest of the six EEG parameters proposed in the study. Similarly, the results obtained suggest that their practical application is different.

- In the case of the parameters derived from Russell's model, they can be used to monitor the emotional state of the ATCO during the development of the exercises. In this part of the research, the data were re-analysed post-simulation. This means that by applying them to real ATC situations, data from past situations can be analysed to learn lessons for the future. The aim is to continue the research so that this analysis can take place in real time. In this way, the cognitive state of the ATCO could be known in live situations, and decisions could be taken accordingly.

- In the case of the engagement and attention parameters, the good numerical results obtained are promising for using these parameters for predictions. Knowing the evolution of the parameters in the last few minutes, it could be of great interest to predict what their value will be in the future. This would allow time to improve the ATCO's performance. Initial prediction tests using the ARIMA method have been carried out on these data. The results are promising. The aim is to continue this analysis and, as in the previous case, to be able to carry it out in real time in the future. This would make the application of these parameters in real ATC situations very useful.

6.3. Limitations in Generalising the Results Obtained

Although the results of the study are promising, two limitations need to be considered when generalising these results. Similarly, the research identified future steps to be developed to address both limitations. These two limitations are the following:

- The first relates to the participants of the study. They are all ATCO students with similar characteristics. The results may vary if the participants change. This limitation was considered from the beginning of the study. The aim of this first phase was to validate the methodology. In the future, now that its usefulness and interest have been demonstrated, the objective will be to extend the simulations to active ATCOs to analyse the differences in the results obtained.
- A second limitation is the laboratory environment in which the research was conducted. Although the participants ran the simulations on a high-fidelity ATC simulation platform and with scenarios created to reflect real traffic, the conditions under which the data were recorded will never be fully equivalent to those of a real operational situation, where pressure is higher, and decisions made can have important consequences. To overcome this, the aim is to continue to apply the methodology to different participants in different simulation scenarios, with the ultimate aim of applying it in real-time operations to analyse the differences between the results obtained.

Notwithstanding these two limitations, the study achieved its initial aims. It has been possible to define a set of six EEG parameters and to demonstrate their usefulness and their relationship with traffic conditions in the sector under the responsibility of the ATCO.

7. Conclusions and Future Work

The purpose of the work presented in this paper was to select six EEG parameters that have the potential to be used in the study of human performance of air traffic controllers in real ATC conditions.

To this end, the parameters excitement, stress, boredom, relaxation, engagement, and attention were defined after an extensive literature review.

The first four EEG parameters are derived from a simplification of Russell's two-dimensional model for classifying emotions. The valence and arousal axes define four quadrants, and each of the parameters is chosen to be representative of one quadrant.

The engagement parameter is obtained from the engagement index formula, and the attention parameter is obtained from the R parameter, which represents the ratio of alpha to beta waves. The equations used to calculate each of the parameters were adapted from previous studies that had yielded interesting results.

The next step was to develop software to automate the calculation of these parameters from the raw data recorded by the EMOTIV Insight headset, i.e., to calculate them from the potential differences between the five active electrodes and the reference electrodes. This paper presented the calculation process in a code developed in MATLAB, as well as some parameters that can be modified by the user for the application of the code in other experiments and different fields.

Once the EEG parameters have been obtained, their relationship with two independent variables that characterise the state of the ATC sector during the simulations have been analysed. These variables were the taskload and the number of simultaneous aircraft in the sector. Both variables were obtained per minute. For this reason, the EEG parameter database obtained from the MATLAB software was obtained with a similar temporal resolution.

The analysis of the variables was carried out in two steps. The first consisted of a basic statistical description of the variables and a graphical analysis of their evolution and behaviour. This was followed by a numerical analysis.

After the graphical analysis, it is concluded that the six EEG parameters showed different behaviours and that it was therefore interesting to include them all in the study.

After the numerical analysis, both for the case of taskload and for the case of the number of simultaneous aircraft, the best results were obtained for the attention and engagement parameters.

Based on the results, it is proposed to use the attention and engagement parameters as variables for the numerical analysis of ATCOs' performance. It is also worth analysing their evolution in relation to ATC events occurring in the ATCO's sector of responsibility. In addition, it is proposed to use the other four parameters in a visual form to gain insight into the emotional state of the ATCO, considering Russell's two-dimensional model.

Furthermore, the objective of selecting parameters that could be explained and whose complete calculation process was explainable has been achieved.

In view of the interesting results obtained, various future works have been proposed to complete the study presented here.

First, in the study presented, the participants were ATCO students. This allowed for a greater number of hours to be spent in the simulator and to validate the methodology for obtaining and analysing the parameters. In the future, work will be carried out to repeat the simulation campaign with active ATCOs with the aim of establishing comparisons between the results obtained in one case and the other.

Regarding the parameters derived from the arousal-valence model, to try to obtain better results from the point of view of correlations and statistical tests, an analysis will be carried out following the methodology expressed in this work but focusing directly on the arousal and valence parameters. The aim is to analyse the influence of each parameter independently on the results obtained.

It is also proposed to continue to include the four parameters presented in the study but to analyse in more detail the time delay observed in the graphs both representing the changes in the taskload and the changes in the EEG parameters.

In view of the promising results for the attention and engagement parameters, initial tests were carried out to establish the possibility of making predictions for these values based on the historical data recorded. The initial results are optimistic and justify the interest to further explore this avenue.

In addition, another future work that has started to be developed is the analysis of the influence of specific ATC events on the different parameters. The aim is to identify which ATC events have the greatest influence on the variation of the parameters. For the time being, work has started on the study of conflicts. This is because these are the ATC events with the highest associated taskload value.

Overall, this study has validated the use of these parameters in very realistic ATC simulated situations and their potential for application in real operational situations, and work will continue to extend it to other participants and other simulation conditions.

Author Contributions: Conceptualisation, M.Z.S. and J.M.M.; methodology, M.Z.S. and R.M.A.V.; software, M.Z.S. and J.M.M.; validation, F.P.M., R.D.-A.J., P.M.L.d.F. and R.M.A.V.; resources, P.M.L.d.F.; data curation, M.Z.S., J.M.M., F.P.M. and R.D.-A.J.; writing—original draft preparation, M.Z.S.; writing—review and editing, J.M.M., F.P.M., R.D.-A.J., P.M.L.d.F. and R.M.A.V.; visualisation, M.Z.S. and J.M.M.; project administration, P.M.L.d.F. and R.M.A.V.; funding acquisition, P.M.L.d.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by a project of collaboration between ATM Research and Development Reference Centre (CRIDA) and Universidad Politécnica de Madrid (UPM). This project is financially managed under the code P2214150422.

Data Availability Statement: Data available on request.

Acknowledgments: The development of this paper is framed within the CRITERIA project (atC event-dRiven capacITy modEls foR aIr nAvigation). This project is framed within a research, development (R&D), and innovation partnership between CRIDA and Universidad Politécnica de Madrid. The authors would like to thank CRIDA for their support in the development of this research line.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

ACC:	Area Control Centre
ATC:	Air Traffic Control
ATM:	Air Traffic Management
ATCO:	Air Traffic Control Officer
CMS:	Common Mode Sensor
CQ:	Contact Quality
CSV:	Comma-Separated Values file
EEG:	Electroencephalography
ESD:	Energy Spectral Density
ROSE:	Radar Operation Simulator and Editor
RTS:	Real-Time Simulations
PSD:	Power Spectral Density

References

1. Isufaj, R.; Koca, T.; Piera, M. Spatiotemporal Graph Indicators for Air Traffic Complexity Analysis. *Aerospace* **2021**, *8*, 364. [CrossRef]
2. Wang, Y.; Hu, R.; Lin, S.; Schultz, M.; Delahaye, D. The Impact of Automation on Air Traffic Controller's Behaviors. *Aerospace* **2021**, *8*, 260. [CrossRef]
3. Li, Q.; Zhang, Y.; Su, R. A Flow-Based Flight Scheduler for En-Route Air Traffic Management. *IFAC-Pap.* **2016**, *49*, 353–358. [CrossRef]
4. Mannino, C.; Nakkerud, A.; Sartor, G. Air Traffic Flow Management with Layered Workload Constraints. *Comput. Oper. Res.* **2021**, *127*, 105159. [CrossRef]
5. Melan, C.; Cascino, N. A Multidisciplinary Approach of Workload Assessment in Real-Job Situations: Investigation in the Field of Aerospace Activities. *Front. Psychol.* **2014**, *5*, 964. [CrossRef] [PubMed]
6. Yeo, L.G.; Sun, H.; Liu, Y.; Trapsilawati, F.; Sourina, O.; Chen, C.-H.; Mueller-Wittig, W.; Ang, W.T. Mobile EEG-Based Situation Awareness Recognition for Air Traffic Controllers. In Proceedings of the 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Banff, AB, Canada, 5–8 October 2017; pp. 3030–3035. [CrossRef]
7. Wang, Y.; Wang, L.; Lin, S.; Cong, W.; Xue, J.; Ochieng, W. Effect of Working Experience on Air Traffic Controller Eye Movement. *Engineering* **2021**, *7*, 488–494. [CrossRef]
8. Balta, E.; Psarrakis, A.; Vatakis, A. The Effects of Increased Mental Workload of Air Traffic Controllers on Time Perception: Behavioral and Physiological Evidence. *Appl. Ergon.* **2024**, *115*, 104162. [CrossRef]
9. Volf, P.; Kutilek, P.; Hejda, J.; Smrcka, P.; Krivanek, V.; Doskocil, R.; Farlik, J.; Casar, J.; Klikova, M. Heart Rate Variability During Long-Term Air Traffic Control in Cadets. In Proceedings of the 2018 41st International Conference on Telecommunications and Signal Processing (TSP), Athens, Greece, 4–6 July 2018; pp. 1–5. [CrossRef]
10. Aricò, P.; Borghini, G.; Di Flumeri, G.; Colosimo, A.; Bonelli, S.; Golfetti, A.; Pozzi, S.; Imbert, J.-P.; Granger, G.; Benhacene, R.; et al. Adaptive Automation Triggered by EEG-Based Mental Workload Index: A Passive Brain-Computer Interface Application in Realistic Air Traffic Control Environment. *Front. Hum. Neurosci.* **2016**, *10*, 539. [CrossRef]
11. Shen, H.; Yu, Y. Robust Evaluation and Comparison of EEG Source Localization Algorithms for Accurate Reconstruction of Deep Cortical Activity. *Mathematics* **2023**, *11*, 2450. [CrossRef]
12. Taheri Gorji, H.; Wilson, N.; VanBree, J.; Hoffmann, B.; Petros, T.; Tavakolian, K. Using Machine Learning Methods and EEG to Discriminate Aircraft Pilot Cognitive Workload during Flight. *Sci. Rep.* **2023**, *13*, 2507. [CrossRef]
13. Izadi Laybidi, M.; Rasoulzadeh, Y.; Dianat, I.; Samavati, M.; Asghari Jafarabadi, M.; Nazari, M.A. Cognitive Performance and Electroencephalographic Variations in Air Traffic Controllers under Various Mental Workload and Time of Day. *Physiol. Behav.* **2022**, *252*, 113842. [CrossRef]
14. Vaid, S.; Singh, P.; Kaur, C. EEG Signal Analysis for BCI Interface: A Review. In Proceedings of the 2015 Fifth International Conference on Advanced Computing & Communication Technologies, Haryana, India, 21–22 February 2015; pp. 143–147. [CrossRef]

15. Guragain, B.; Rad, A.B.; Wang, C.; Verma, A.K.; Archer, L.; Wilson, N.; Tavakolian, K. EEG-Based Classification of Microsleep by Means of Feature Selection: An Application in Aviation. In Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23–27 July 2019; pp. 4060–4063. [CrossRef]
16. Hernández-Sabaté, A.; Yauri, J.; Folch, P.; Piera, M.À.; Gil, D. Recognition of the Mental Workloads of Pilots in the Cockpit Using EEG Signals. *Appl. Sci.* **2022**, *12*, 2298. [CrossRef]
17. Kouba, P.; Šmotek, M.; Tichý, T.; Kopřivová, J. Detection of Air Traffic Controllers' Fatigue Using Voice Analysis—An EEG Validation Study. *Int. J. Ind. Ergon.* **2023**, *95*, 103442. [CrossRef]
18. Borghini, G.; Aricò, P.; Di Flumeri, G.; Cartocci, G.; Colosimo, A.; Bonelli, S.; Golfetti, A.; Imbert, J.P.; Granger, G.; Benhacene, R.; et al. EEG-Based Cognitive Control Behaviour Assessment: An Ecological Study with Professional Air Traffic Controllers. *Sci. Rep.* **2017**, *7*, 547. [CrossRef] [PubMed]
19. Subha, D.P.; Joseph, P.K.; Acharya, U.R.; Lim, C.M. EEG Signal Analysis: A Survey. *J. Med. Syst.* **2010**, *34*, 195–212. [CrossRef] [PubMed]
20. Wan Ismail, W.O.a.S.; Hanif, M.; Mohamed, S.B.; Hamzah, N.; Rizman, Z.I. Human Emotion Detection via Brain Waves Study by Using Electroencephalogram (EEG). *Int. J. Adv. Sci. Eng. Inf. Technol.* **2016**, *6*, 1005–1011. [CrossRef]
21. Herwig, U.; Satrapi, P.; Schönfeldt-Lecuona, C. Using the International 10–20 EEG System for Positioning of Transcranial Magnetic Stimulation. *Brain Topogr.* **2003**, *16*, 95–99. [CrossRef]
22. Mishra, A.; Shrivastava, K.K.; Quadir, N.A. Reducing Commercial Aviation Fatalities Using Support Vector Machines. In Proceedings of the 2019 International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 27–29 November 2019; pp. 360–364. [CrossRef]
23. Contact Quality (CQ) vs. EEG Quality (EQ). Available online: https://emotiv.gitbook.io/emotivpro-v3/emotivpro-menu/contact-quality-map/contact-quality-cq-vs.-eeg-quality-eq#how-is-eeg-quality-different-to-contact-quality (accessed on 17 October 2023).
24. Zamarreño Suárez, M.; Arnaldo Valdés, R.M.; Pérez Moreno, F.; Delgado-Aguilera Jurado, R.; López de Frutos, P.M.; Gómez Comendador, V.F. Methodology for Determining the Event-Based Taskload of an Air Traffic Controller Using Real-Time Simulations. *Aerospace* **2023**, *10*, 97. [CrossRef]
25. Li, T.; Lajoie, S. Predicting Aviation Training Performance with Multimodal Affective Inferences. *Int. J. Train. Dev.* **2021**, *25*, 301–315. [CrossRef]
26. Wei, F.; Wu, D.; Chen, D. An Investigation of Pilot Emotion Change Detection Based on Multimodal Physiological Signals. In Proceedings of the 2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology (ICCASIT, Weihai, China, 14–16 October 2020; pp. 1029–1034. [CrossRef]
27. Truschzinski, M.; Valtin, G.; Müller, N.H. Investigating the Influence of Emotion in Air Traffic Controller Tasks: Pretest Evaluation. In *Engineering Psychology and Cognitive Ergonomics: Performance, Emotion and Situation Awareness*; Harris, D., Ed.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2017; Volume 10275, pp. 220–231, ISBN 978-3-319-58471-3.
28. Patel, P.; Annavarapu, R.N. EEG-Based Human Emotion Recognition Using Entropy as a Feature Extraction Measure. *Brain Inform.* **2021**, *8*, 20. [CrossRef]
29. Russell, J.A. A Circumplex Model of Affect. *J. Pers. Soc. Psychol.* **1980**, *39*, 1161–1178. [CrossRef]
30. Kim, J.; Andre, E. Emotion Recognition Based on Physiological Changes in Music Listening. *IEEE Trans. Pattern Anal. Mach. Intell.* **2008**, *30*, 2067–2083. [CrossRef] [PubMed]
31. Giraldo, S.; Ramirez, R. Brain-activity-driven real-time music emotive control. In Proceedings of the 3rd International Conference on Music & Emotion (ICME3), Jyväskylä, Finland, 11–15 June 2013.
32. Hwang, S.; Jebelli, H.; Choi, B.; Choi, M.; Lee, S. Measuring Workers' Emotional State during Construction Tasks Using Wearable EEG. *J. Constr. Eng. Manag.* **2018**, *144*, 04018050. [CrossRef]
33. McMahan, T.; Parberry, I.; Parsons, T.D. Evaluating Player Task Engagement and Arousal Using Electroencephalography. *Procedia Manuf.* **2015**, *3*, 2303–2310. [CrossRef]
34. Hasegawa, C.; Oguri, K. The Effects of Specific Musical Stimuli on Driver's Drowsiness. In Proceedings of the 2006 IEEE Intelligent Transportation Systems Conference, Toronto, ON, Canada, 17–20 September 2006; pp. 817–822. [CrossRef]
35. Thakor, N.V.; Tong, S. Advances in Quantitative Electroencephalogram Analysis Methods. *Annu. Rev. Biomed. Eng.* **2004**, *6*, 453–495. [CrossRef]
36. Bastos-Filho, T.F.; Ferreira, A.; Atencio, A.C.; Arjunan, S.; Kumar, D. Evaluation of Feature Extraction Techniques in Emotional State Recognition. In Proceedings of the 2012 4th International Conference on Intelligent Human Computer Interaction (IHCI), Kharagpur, India, 27–29 December 2012; pp. 1–6. [CrossRef]
37. Hamid, N.H.A.; Sulaiman, N.; Murat, Z.H.; Taib, M.N. Brainwaves Stress Pattern Based on Perceived Stress Scale Test. In Proceedings of the 2015 IEEE 6th Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, 10–11 August 2015; pp. 135–140. [CrossRef]
38. Blanca, M.J.; Alarcón, R.; Arnau, J. Non-Normal Data: Is ANOVA Still a Valid Option? *Psicothema* **2017**, *29*, 552–557. [CrossRef]