TPM Vol. 32, No. S4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

MENTAL WORKLOAD MEASUREMENT IN CONTROL SYSTEM ENGINEERS USING EEG INDICES

DOC. MONIZA NUREZ KHAN[1], VIJAY SHANKAR YADAV[2], DR. RITU TALWAR[3]
[1]ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
e-mail:ku.monizanurezkhan@kalingauniversity.ac.in,0009-0004-9879-6445
[2]ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
e-mial:ku.vijayshankaryadav@kalingauniversity.ac.in0009-0001-2485-3177
[3]ASSISTANT PROFESSOR, NEW DELHI INSTITUTE OF MANAGEMENT, NEW DELHI, INDIA.,
e-mail: ritu@ndimdelhi.org, https://orcid.org/0000-0002-8617-4479

Abstract
In control system environments, there are high levels of sustained attention, decision making, problem solving, as well as time-sensitive and high-stakes considerations. Cognitive functions that induce high levels of mental workload on engineers, and may contribute to human error, fatigue, and compromised system safety, if left unmonitored. Therefore, understanding mental workload as well as quantifying mental workload will aid in creating adaptive interfaces and improving overall operational efficiency. This study documented the use of electroencephalography (EEG) as a non-invasive neurophysiological measure of mental workload in control system engineers. EEG measures provide insight that are real-time, objective indicators of cognitive demands because the electroencephalogram measures through changes in brain activity expressed differently by varying task loads or intensities. In this study, participants completed simulated control system tasks that simulated routine and emergencies. Continuous EEG data were recorded throughout the demonstration, and data collected during emergencieswere the focus of the analysis. In addition to event-level analysis of demand/workload through a reanalysis of the EEG data, key indicators used to estimate participants' workload were frontal theta power and parietal alpha suppression while engaging in control system tasks, as these measures correlate well with mental effort and attentional regulation. Results found EEG workload patterns that distinguished cognitive load according to varying levels of task complexity and task duration; with more complex tasks and tasks of longer duration created higher workload in terms of theta activity and lower workload in terms of alpha power. Overall, the findings of this study highlight the potential of EEG-based monitoring in real-time in operational settings to detect mental overload before performance decline. The study highlights critical implications for enhancing human reliability, preventing fatigue-related errors, and informing the development of intelligent workload-aware systems in complex operational environments.
Keywords: EEG, Mental Workload, Cognitive Load, Control Systems, Brainwaves, Neuroergonomics, Human Reliability.

I. INTRODUCTION

Mental workload corresponds to the amount of cognitive demand necessary to carry out a task, particularly in high-demand environments such as during an occupation with high demand on prolonged attention, rapid-fire decision-making, and multitasking [1]. In control systems environments, whether in industrial automation, power plants, or air traffic control, engineers need to monitor real-time dynamic systems in high-pressure situations, which contributes to extreme cognitive cost. Given that the dynamic systems are complex, it is easy to surmise that any errors in attention and decision-making can result in catastrophic failure. Understanding mental workload and how to measure it is necessary in these environments to increase performance reliability and decrease risk to systems and humans. A potentially effective tool for evaluating mental workload is Electroencephalography (EEG), which allows for non-invasive, real-time monitoring of the brain's electrical activity. EEG or neural assessments remove the subjectivity of self-reported levels of cognitive activity and provide ongoing, physiological assessment of the brain's response to the task demands of limitations of their occupations [2]. Evidence in the use of EEG to measure mental workload is still very limited, both in terms of not developing a general neuropsychological framework to assess an engineer's mental workload in real-time work environments [6]. Most of the studies focused on one specific field (aviation, medical, etc.) and only recently began exploring how control system engineers neurologically respond to various task complexities, making this population one that has yet to be evaluated in terms of how different task complexities impact mental workload. This study seeks to address that gap by posing two key research questions: Can EEG reliably measure mental workload variations in control system engineers? And what neural patterns are consistently observed across different phases of cognitive task execution?[3][14]

II. NEUROCOGNITIVE BASIS OF WORKLOAD

2.1. Brainwave Signatures of Mental Workload

A thorough understanding of mental workload must be grounded in neurocognitive processes that underlie mental task performance, in particular, the electrical activity of the brain while performing tasks [7]. Timing and volitional tasks induce EEG-related electrical brain activity, providing a means to identify changes in neural electrical activity that can distinguish between the cognitive states associated with the cognitive demands of the task. These electrical signals are arranged as frequency bands which contribute travel to subjective cognitive demands for a given task to include: theta waves (4 - 7 Hz) most pronounced in the frontal cortex of the brain, are associated with memory load and cognitive processing; alpha waves (8 - 12 Hz) typically displayed by the parietal regions of the brain, alpha power decreases as the mental loads associated with the tasks increase, signalling reduced relaxation and increased attention; and beta waves (13 -30 Hz), our most active cognitive thoughts, attentional resource/action, and task performance. Thus, cognitive tasks and demands will change the electrical activity of the brain, which ultimately results in measurable indices of mental workload [11].

2.2. Theoretical Models Supporting Cognitive Load Assessment

A crucial component when assessing cognitive workload is the use of the P300 event-related potential (ERP). The P300 is a positive wave occurring approximately 300 ms after an infrequent stimulus has been presented. As such, reduced P300 amplitude is often recognized as auditorially focusing, while mental fatigue and decreased visual or orienting attention processing occur. In parallel, neural signatures such as frontal theta power change directionally as a potential continuous insight to sustained cognitive engagement. With the use of these neural processes, one can continuously monitor mental effort rather than rely solely on zero or interval self-reports and behaviour assessments [8]. Alternatively, from a theoretical instantiation, two key foundational principles establish the ability to classify with working load mental activity. Cognitive Load Theory (CLT) conceptualizes constraints on embedded working memory and performance that occur under a differential context of cognitive load through one's actions and types of loads (intrinsic, extraneous, and germane). Meanwhile, Multiple Resource Theory (MRT) explains how competing demands on shared cognitive resources can impair efficiency [10]. Together, these theories and neurophysiological markers form the basis for quantifying and interpreting mental workload using EEG.

III. PSYCHOLOGICAL AND APPLIED NEUROSCIENCE CONTEXT

During the last 20 years EEG EEG-based studies have received growing attention and value for assessing mental workload in high-stakes environments, such as air traffic control, military set-ups, and commercial aerospace navigation. The human operators in these situations must sustain continuous vigilance, manage multiple streams of information, and make decisions under time pressure, as they have a high workload. Researchers have clearly shown that EEG can provide a reliable and real-time alternative to assessing workload using pre-existing or new tools used in the verification process [9]. For instance, in military simulations, more frontal theta activity (4-7 Hz) is linked with increased demands of the tasks that operators are performing, and decreased parietal alpha power (8-12 Hz) corresponds with maintaining attention to a task during pilot training exercises [5].

This body of work is distinct in the emerging field of neuroergonomics, which is where neuroscience meets human factors engineering,to build systems that facilitate human performance and allow for better designs. The important concept is that we can design systems that apply new neurophysiological bottom-up approaches, which permit operators to effectively task-brain states in real-time, rather than simply providing feedback using traditional assessment methods to learn how the operator was functioning. Neuroergonomics provides opportunities for a "future-proof" workload. This is especially important in safety-critical employment like control system engineering [13].

Regardless of the promise of these possible techniques, we continue to see subjective workload measurement tools, such as NASA-TLX, continue to be perhaps the most widely utilized methods for measuring workload. Self-report protocols are often useful; however, self-reports ask for retrospective measures, which introduces bias and often limitsthe immediacy of the work being performed. EEG, on the other hand, allows for continuous, objective, and direct insight into cognitive processing and thus represents a more reliable means of understanding mental workload in dynamic operational contexts.

IV. PARTICIPANT AND EXPERIMENTAL DESIGN

The data were collected from a sample of control system engineers with varied experience who would provide variation in cognitive response to the study. The experiments occurred in a controlled, simulated control room environment that closely resembled real-time monitoring and decision-making. Participants completed two cognitive tasks, routine task and emergency task, to trigger different cognitive workload scenarios [12]. EEG data were collected with a multi-channel EEG device with electrodes placed according to the 10-20 international system to capture electrical signals at a continuous sampling rate for a practically fixed time period during each pseudonymized session [4]. Ethical approval was requested and granted for the data collection. All participants provided informed consent and psychological safety and comfort of participants were the focus of this study [15].

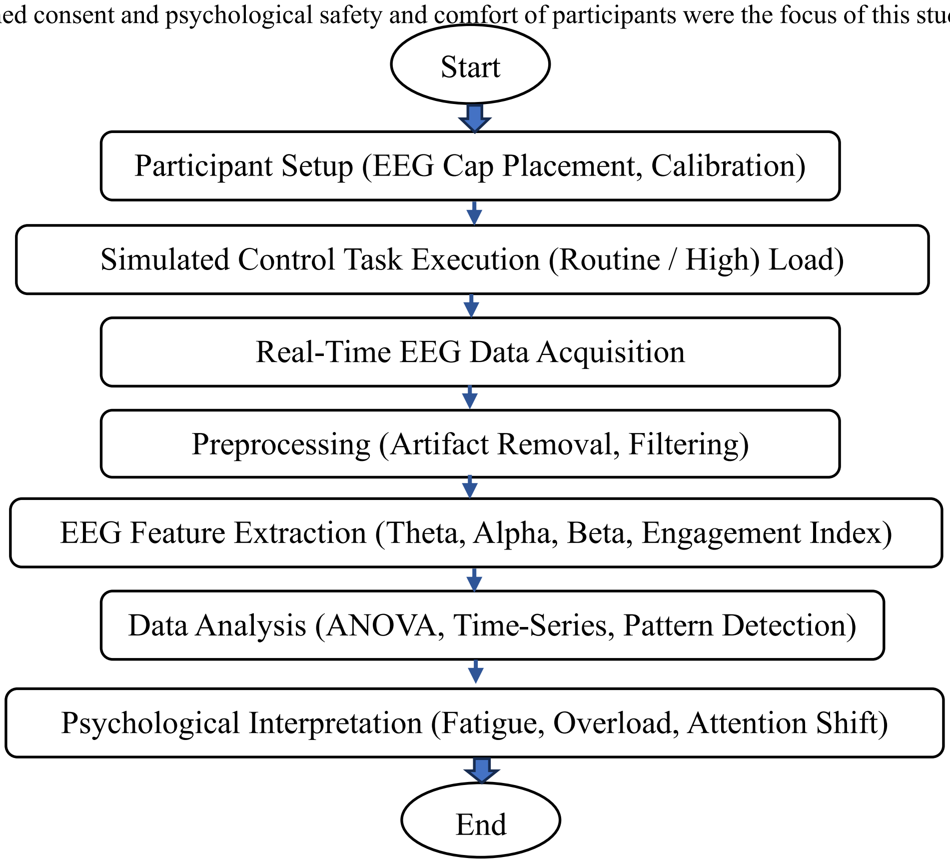

Figure 1: Experimental Workflow for EEG-Based Mental Workload Assessment

Figure 1 represents the experiment overall in how mental workload is measured in control system engineers using EEG. Participant preparation works as the first step. The evaluation considers simulated routine and emergency tasks and all EEG signals were collected/recorded, de-artifacted, feature extracted (theta, alpha, beta and engagement indices) and statistically analyzed before interpretation of cognitive states such as overload and fatigue. The evaluation concludes with insights generated by participant performance and cognitive dynamics to inform designs from an adaptive system perspective for operator support.

V. EEG INDICES AND DATA COLLECTION PROCEDURES

In order to measure mental workload in control system engineers accurately, EEG data collection shall be performed under controlled conditions and also follow rigorous protocols for pre-processing. Each participant was fitted with an EEG cap conforming to the international 10–20 standard, and in particular, electrodes were placed above all of the frontal and parietal lobes for our analyses of task performance. Participants were able to perform the task while EEG signals were continuously recorded while they interacted with simulated control system interfaces that represented different levels of cognitive demand.

In order that we could believe the accuracy of the final analysis, the raw EEG data were processed in several pre-processing steps to provide spatially and temporally clear signals. Artifact rejection was performed to eliminate the noise signal caused by movements such as eye blinks, facial muscle movements, and electrical disturbances in the raw signal. Once the signals had been pre-processed and artifacts removed, independent component analysis (ICA) Then, band-pass filtering was performed to isolate our bands of interest.

Table 1: Comparison of EEG Workload Indices Across Task Conditions

Task Condition	Frontal Theta (μV^2)	Parietal Alpha (μV^2)	Engagement Index (β / [$\alpha + \theta$])
Low Cognitive Load	3.4 ± 0.7	8.1 ± 1.0	0.72
High Cognitive Load	6.1 ± 1.2	5.2 ± 0.9	1.18

Table 1 compares frontal theta power, parietal alpha power, and the engagement index of workload metrics derived from EEG with different task conditions (low-load and high-load) so that the neural differences in cognitive demand experienced by control system engineers during simulation tasks can be compared. Frontal theta and parietal alpha were shown to be augmented under high workload conditions, indicative of increased cognitive effort and attentional demand, as the engagement index. Engagement index is the only composite measure provided from this table, and this showed a marked increase in engagement index associated with high-load conditions. Table 3 is a quick reference for summarizing neural workload responses and represents direct evidence to assist the interpretation of cognitive load changes required by the task according to EEG neural data.
In experiments incorporating eye-tracking, gaze data were analyzed alongside EEG to improve contextual interpretation of gaze use, particularly in situations requiring intense visual monitoring.Sensorial presence provided a greater capacity for evaluating cognitive load and attentional engagement. Important EEG workload indices that were extracted from the cleaned data included: Frontal Theta Power, which was shown to increase during periods of high cognitive computational load and decision-making. Parietal Alpha Suppression: reflects both visual-spatial vigilance and a decrease in cognitive relaxation; Engagement Index (EI): = Beta / (Alpha + Theta); is an assessment of mental effort and sustained attention. Task Load Index (TLI): a compound of dynamic metrics showing variations of workload during the execution of the tasks. Together, these indices provide a multi-dimensional proxy of mental workload, offering insight into the 'general' over time, rather than only measuring spikes or transient cognitive states in real time.

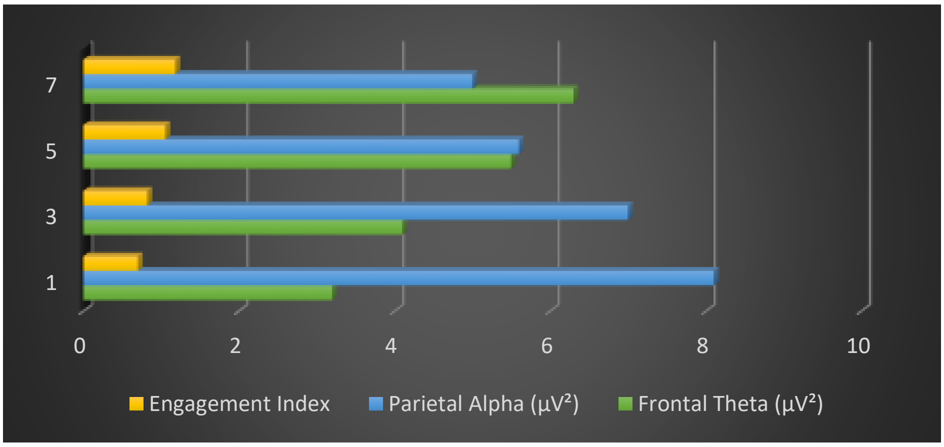

Figure 2: Real-Time Mental Workload Fluctuations During Task Performance

Figure 2 depicts the changes over a 5-minute simulated control system task for three prominent EEG indices: Frontal Theta, Parietal Alpha, and Engagement Index. The x-axis values constitute time (in minutes) while the y-axis values represent the normalized EEG values (arbitrary units). In this case, one image shows a complete picture of cognitive load as shown by theta and engagement peaks at mental effort increases, while the dip in alpha indicates a corresponding drop in relaxation (and possible increase in attention).

VI. DATA INTERPRETATION AND PSYCHOLOGICAL IMPLICATIONS

The EEG data collected in the simulated control tasks were analyzed and examined through several statistical and computational methodologies, all based on the workload patterns we could not identify. In analyzing the EEG indices, ANOVA and correlation matrices allowed us to see disaggregation of EEG activity differently across phases of reference experiments and groups of participants, while time-series analysis also considered workload over time. The cluster analysis expands upon the previous analysis, making the distinction between engagement/activity of the brain between high-load and low-load tasks, where there was an identifiable shift in cognitive engagement. These outcomes were portrayed and visualised in a usablemanner through heat maps of the activity of the electrode during the tasks and timeline graphs demonstrating periods of cognitive fatigue, disengagement, or recovery.

From a psychological perspective, the results provide insight into the response of control system engineers to continuous mental effort, as several periods of sustained frontal theta activation (increases in cognitive demand) were observed, and alpha suppression (visually intensive task) appeared to occur together. Where reductions in beta activity occurred, it indicated moments of underload or disengagement, with the engineer's attention lapsed, or insufficient cognitive processing time before taking another action. As a preliminary study, this encourages potential thresholds, where performance can be degraded and counting errors can occur, once exceeded the thresholds; and while being able to observe continuously EEG accompaniment related to workload could provide the basis for adaptive interfaces that react to mental state changes, we could reduce human error and improve system safety. Limitations will persist, particularly in moving situations where there is a reasonable expectation of introduced artifacts to the EEG signal; however, taken as a whole, this approach could support burnout prevention and mental health monitoring interventions, while providing support for individuals in demanding and high-risk occupational groups.

VII. CONCLUSION

This investigation provides evidence that EEG is a useful and effective method for measuring mental workload in control system engineering settings. EEG measures and records a human's neural activity as it occurs, a key difference between EEG and traditional subjective indicators. EEG provides insight into cognitive load that may not be possible to obtain through traditional subjective measures. This research confirms the usefulness of EEG monitoring to gauge mental strain, but likely even more important is the implications of EEG monitoring for design and operations. Integrated EEG monitoring of mental workload for evaluating a system's design could imply more user-friendly and responsive control systems, subsequently leading to decreased error by humans, better performance, and training that could be even more closely tailored for individual models of experience. This investigation could also be used to develop computational adaptive control systems for characterizing and deploying to engineer cognitive state, a potential to optimize workload, while monitoring for overwhelming states quickly. With cognitive demands in technological advances becoming more complex, using neurophysiological data to guide system design is important to support human operators in collaboration and ultimately keep them safe over long-time spans of control.

REFERENCES

[1] HAJJAJI, S. E., & M'barki, M. A. (2018). The Higher Education Quality Concept: Comparative Analysis between the Universities of Morocco and Spain. *International Academic Journal of Innovative Research*, *5*(1), 1–8. https://doi.org/10.9756/IAJIR/V5I1/1810001

[2] Fathima Sapna, P., & Lal Raja Singh, R. (2022). Smart Meter Data based Load Analysis Using Clustering Technique. *International Academic Journal of Science and Engineering*, *9*(1), 39–48. https://doi.org/10.9756/IAJSE/V9I1/IAJSE0918

[3] Delgosha, M. S., Rokni, A., Seyyedan, S. A., Omrani, L., & Zadeh, E. P. (2017). The Study of the Effect of Hypnosis on the Reduction of Job Stress among Nurses. *International Academic Journal of Social Sciences*, *4*(2), 84–89.

[4] Dusi, P. (2025). Blockchain-enabled security framework for cross-platform IoT interoperability. Electronics, Communications, and Computing Summit, 3(1), 11–21.

[5] Mirabi, M., & Lahti, E. (2025). Graph signal processing-based interference suppression for multi-user massive MIMO systems. Electronics, Communications, and Computing Summit, 3(2), 56–61.

[6] Kumar, T. M. S. (2025). Comparative analysis of Hatha Yoga and aerobic exercise on cardiovascular health in middle-aged adults. Journal of Yoga, Sports, and Health Sciences, 1(1), 9–16.

[7] Tamannaifar, M., & Golmohammadi, S. (2014). Comparison of Psychological Well-Being and Job Stress between Teachers of Special and Ordinary Schools in Isfahan City. *International Academic Journal of Organizational Behavior and Human Resource Management*, *1*(1), 18–27.

[8] Carter, E., & Heinriksen, L. (2023). Performance Analysis of Ceramic Membranes in Treating Textile Wastewaters. *Engineering Perspectives in Filtration and Separation*, *1*(1), 13-15.

[9] Ghazo, M. M. (2025). Integrating Circular Economy and Sustainability: A Strategie Assessment of Organizational Practices in Jordan. Calitatea, 26(205), 9-14.

[10] Mehta, A., & Singh, R. K. (2025). Targeting Tumor Microenvironment in Metastatic Cancer. In *Medxplore: Frontiers in Medical Science* (pp. 1-18). Periodic Series in Multidisciplinary Studies.

[11] Malhotra, A., & Joshi, S. (2025). Exploring the Intersection of Demographic Change and Healthcare Utilization: An Examination of Age-Specific Healthcare Needs and Service Provision. *Progression Journal of Human Demography and Anthropology, 3*(1), 8-14.

[12] Rajeev, S. (2023). An Analysis of NEP 2020: Certain Key Issues. *Indian Journal of Information Sources and Services*, *13*(1), 10–16. https://doi.org/10.51983/ijiss-2023.13.1.3443

[13] Akrami, R., Chitsaz, H., & Ahmadi, Z. (2024). Effect of dietary dehydrated sour lemon peel (Citrus limon) powder on metabolic enzymes, serum biochemistry and stress status of rainbow trout (Oncorhynchus mykiss) juvenile. *International Journal of Aquatic Research and Environmental Studies*, *4*(1), 91-99. http://doi.org/10.70102/IJARES/V4I1/8

[14] Abdullah, D. (2025). Nonlinear dynamic modeling and vibration analysis of smart composite structures using multiscale techniques. Journal of Applied Mathematical Models in Engineering, 1(1), 9–16.

[15] Moretti, A., & Tanaka, H. (2025). Securing Multi-Modal Medical Data Management System using Blockchain and the Internet of Medical Things. *Global Journal of Medical Terminology Research and Informatics*, *3*(1), 15-21.

[16] Pandey, V., & Gupta, N. (2024). Mechanical Engineering Design: A Multidisciplinary Approach. *Association Journal of Interdisciplinary Technics in Engineering Mechanics*, *2*(4), 6-11.

[17] Vivas, D. E. D., Pena, W. Y. G., Botero, S. P. C., & Rojas, A. E. (2024). A Controlled Phishing Attack in a University Community: A Case Study. Journal of Internet Services and Information Security, 14(2), 98-110. https://doi.org/10.58346/JISIS.2024.I2.007

[18] Subbaiah, S., Agusthiyar, R., Kavitha, M., & Muthukumar, V. P. (2024). Artificial Intelligence for Optimized Well Control and Management in Subsurface Models with Unpredictable Geology. *Archives for Technical Sciences*, *2*(31), 140–147. https://doi.org/10.70102/afts.2024.1631.140