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REAL TIME STRESS MONITORING IN PROGRAMMABLE LOGIC CONTROLLER TECHNICIANS

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Abstract
The presentation looks at the real-time monitoring of stress of PLC technicians, the advanced PLC workers in today industrial automation. PLC technicians have come a need to do systems diagnostics, control logic reprogramming, and production-sustaining emergency response in diagnosis control systems within tight deadlines. In addition to commanding a high level of professional expertise, these processes require deep cognitive and emotional stamina. As an example, performance assessments, productivity evaluations, and even subjective self-evaluations do not capture the significant internal, psychological, and physiological stress of the high-stakes operations faced by the technicians.
This methodology gap is addressed by conducting the current research within smart factory simulations equipped with wearable biosensing technologies, EEGs, HRVs, and GSRs. These devices monitor and record cognitive stress, neural, cardiovascular and electrodermal signals, and emotional arousal. In a controlled setting, twenty qualified PLC technicians were given tasks and asked to perform to the best of their abilities starting from simple to complex: routine maintenance, fault detection and correction, and ending with the most complex - critical error management. Each stage was designed to increase the mental workload step by step in terms of focus, memory, decisional analysis, and emotional control.
The research findings show that there is a noteworthy relationship between the difficulty of the task and the physiological signs of stress. High-complexity tasks were marked by heightened EEG beta activity, increased GSR conductivity, and lowered HRV. These biofeedback metrics exemplified the effectiveness of biosensing in monitoring and evaluating stress in real-time. Besides, the findings highlight the feasibility of creating adaptive automation systems that would react to an operator's stress by modifying the task, providing cognitive help, or activating safety measures.
Apart from the technical aspects, the paper tackles critical societal issues regarding the use biometric data, such as the use of biometric data and the need for informed consent, data protection, non-bias, and design opacity. It argues for the proactive monitoring of stress within the industrial framework to promote the enhancement of human well-being, safety, and effectiveness, advocating for the protective stress monitoring systems. The research considers real-time cognitive-emotional tracking as an initial element for the forthcoming human-focused industrial automation.
Keywords: Real-Time Data Analysis, Wearable Devices, Employee Stress Evaluation, Automatic Behavior Recognition, PLC Techs, HRV, GSR, EEG

1. INTRODUCTION

The introduction recognizes the PLC-related position's specific cognitive workload and the PLC's human interface for technicians as the cognitive workload PLCs impose on operators. Continuous attention monitoring, and intricate processing such as error debugging, logic rewrites, and responding to failures in the systems within seconds are duties handled by human technicians. As the work mechanics evolve towards digital, knowledge-related, and automated systems, self-evaluations and productivity logs become obsolete gauges for real-time workload and stress monitoring [1]. The above challenges can be addressed by the most recent developments in wearable biosensors that allow monitoring of stress biomarkers, such as brainwaves, cardiac variability, and skin conductivity [13]. This is to say, the gap is formulated by the biosensor technology for real-time stress detection and monitoring, motivating the need for the stress detection technology, and providing an analysis of the overlooked gap [7]. Most importantly, it provides the focus and rationale for the study concerning the stress biosensors alongside occupational safety, human-machine interaction, cognitive ergonomics, and automation. This part of the introduction puts the focus on the need-for and the gap-to-fill, watchdogs on the study and its purpose, alongside determining the structure of the paper and objectives on real-time stress detection technology impact on data interpretation, task management interface design and automation of responsive systems [5].

1.1 The Evolving Nature of PLC Technician Work

Today's PLC technicians work in a fully digitized environment where the integrity of the system depends on swift decision-making and real-time logic programming. Their work has shifted to system automation diagnostics from physical system automation repairs. The high level of responsibility and the severe consequences of a fault correction escalate cognitive overload and emotional stress [8]. Conventional methods of stress evaluation, using checklists or observation, are inapplicable and void of real-time responsiveness and objectivity [9]. The high stakes of constant focus and the need for awareness within a given timeframe in PLC programmed automation processes create the need for devices such as stress wearables to monitor cognitive exhaustion and industrial error fatigue [6].

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This part focuses on the cognitive workload, wearable technology, and stress indicators physiology related to stress measurement in an industrial setting. It outlines the progression from various stress measurement techniques like surveys and performance logs to modern monitoring systems which are real-time, sensor-based, non-invasive, and precise [2] [4]. Other focus areas include neuroergonomics which is the study of work-related brain functions and the application of biosensors, like EEG, HRV, and GSR, in the workplace [15].

This review also defined unexplored research areas such as: PLC technicians, customizable task monitoring models, and stress classification using multi-modality data fusion [3]. It also defined the construct which the research was based on: a stress inputs (task complexity, time pressure) to physiological outputs brain, cardiac and skin signals and performance metrics (error rate, reaction time) model. This model underpins the creation of adaptive support systems and rationalizes the experimental methodology used.

2.1 Real-Time Biosensing for Stress: A Multimodal Perspective

Multimodal biosensing integrates EEG, HRV, and GSR for better accuracy in stress detection and identification triggered by a specific event [11]. EEG records electrical impulses from the brain associated with concentration and fatigue, HRV shows the response of the sympathetic nervous system, and GSR shows the amount of skin conductance related to emotions [14]. Together, these sensors enhance understanding of a technician's stress level [10]. This makes it possible to interpret mental processes in real-time during demanding activities like logic programming or emergency response. Compared to single sensor systems, multimodal systems provide improved reliability, greater sensitivity to context, and stronger signals or feedback," especially for cognitively-aware automated systems in industrial settings [12].

3. METHODOLOGY

The described methodology focuses on the experimental setup created to assess the real-time stress levels of PLC technicians using wearable biosensors. An Simulated Industrial Control Laboratory was created to mirror the environments technicians face during real-time automation system workflows. Participants with basic to intermediate experience in PLC settings were recruited to participate in the study. This group of technicians completed well-defined control tasks at routine, moderate, and high levels of cognitive demand—control tasks to manage routine processes, and, in some cases, emergency faults to manage real-time systems within strict time windows. Throughout the tasks, participants' EEG, heart rate variability (HRV), and galvanic skin response (GSR) were monitored.

Data acquisition were synchronized with the Lab Streaming Layer (LSL) computation, which guarantees temporal alignment across signals in time-series collection. To counterbalance order effects and fatigue, randomization of tasks was implemented, and breaks were introduced between block structures. Subjective data were collected immediately after completing the tasks using the NASA-TLX, which was analyzed in comparison to biosensor results. The section also describes processes of signal denoising, normalization, and feature extraction. Ethical protocols included provision of informed consent, data anonymization, and allowing breaks from tasks ensuring the comfort of participants during the study. This section demonstrates that the approach was ecologically valid, replicable, and optimally designed to assess stress variability within diverse PLC tasks.

3.1 Task Design Across Cognitive Load Conditions

Tasks were sorted into three tiers based on intricacy: (1) Low – basic ladder logic step execution, (2) Moderate – real-time troubleshooting, and, (3) High – fault identification under time constraints. Each tier simulated realistic industrial scenarios. For example, sensor misfires, wiring errors, and communication dropouts. To induce progressively more intense physiological stress responses, time limits and problem-solving hurdles were added. Stress markers were continuously monitored as counterbalanced tasks were performed. This stratified method not only allowed for the differentiation of stress load, but also classification with biosensor data, providing essential information for real-time stress modeling and adaptive workload strategy in PLC environments.

4. RESULTS AND DISCUSSION

Analyzing multimodal biosensor data showed marked differences in physiological stress markers with different complexity levels. EEG data revealed increased frontal theta and suppressed alpha activity during high-stress conditions, suggesting higher levels of cognitive engagement and concentration. In the HRV analysis, there was a drop in RMSSD with a concurrent increase in LF-HF ratio, suggesting increased sympathetic stress under time pressure. GSR data also confirmed emotional arousal with increased skin conductance during fault-handling tasks.

Findings are consistent with the NASA-TLX ratings provided, thus establishing the credibility of the physiological metrics. Integrated sensor data produced with machine learning classifiers SVM and Random Forest achieved above 85% accuracy in predicting stress levels. The discussion focuses on the integration of EEG, HRV, and GSR and their paced out real-time adaptability and monitoring in precise automation jobs. It also discusses the possible relationship between physiological adaptability and the performance of the technician, proposing that these metrics could help develop systems with customizable workloads tailored to the individual's performance capabilities. Overall, the study affirmatively validated the developers' proposition of the stress monitoring device's wearable application during work hours for PLC technicians within the context of optimized performance, recovery of mental and emotional balance, and active emotional self-regulation in high-risk industrial environments.

4.1 Sensor Concordance and Stress Prediction Accuracy

Cross-modal analysis validated robust interrelations of EEG, HRV, and GSR readings. During intense troubleshooting assignments, peak stress moments were in alignment across all sensors. Classification accuracy of stress levels using combined features was greater than using individual sensors, which confirms the hypothesis of the need for multimodal integration. Participants with higher cognitive adaptability manifested lower stress variability and higher task success. These findings confirm the potential of the system for real-time stress classification and profiling technician readiness. The insights gleaned from biosensors not only forecast current stress but also enable anticipatory actions, advancing the possibility of real-time adaptable automation in PLC-based environments.

5. INDUSTRIAL IMPLICATIONS

The use of real-time stress assessment systems for PLC field service engineers has significant industrial impacts. With the increasing and more sophisticated automation of industries, the emotional and mental health of the PLC technician is critical for system uptime and safety. This research envisions the stress monitoring system to be integrated with HMIs, which will enable HMIs to adapt dynamically as the technician's stress biometrics change—suggesting automated displays, issue "take a break" alerts, or task reassignment of climactic or intricate tasks. For example, if a PLC technician's stress biometrics surpass a certain limit, non-essential notifications could be silenced to allow for recovery. In addition to aiding in task prioritization, these data can help in the design of stress management training programs where participants who demonstrate high stress from specific task performance receive comprehensive assistance or retraining.

The data can also enable stress-informed scheduling by not assigning high workload tasks during identified high fatigue periods. In addition, performance evaluation of the PLC technician and engineers could be improved with the use of biometric indicators in addition to relying solely on performance records. These systems can provide improved safety, reduced error rates, and optimized technician retention. However, these systems have to be industrially deployed which requires the technician to have full visibility, protective measures, and need to be compliant to labor standards to prevent abuse. Following these guidelines. These systems can improve automation productivity, while safeguarding technician well-being in complex automated environments.

5.1 Cognitive-Aware Human-Machine Interface Design

Real-time stress detection allows for more responsive and secure automation systems. Automation systems equipped with stress monitors—through the technician's EEG or HRV—can temporarily relax automated functions or recommend breaks. Such responsiveness enhances the technician's stress decision-making capability and minimizes costly mistakes or omissions. Stress responsive HMIs enhance productivity and mental resilience, and improve safety, especially with PLC systems overseeing essential services. This part argues for the application of cognitive ergonomics in interface design to create intelligent industrial systems.

6. ETHICAL AND FUTURE CONSIDERATIONS

The use of biosensors like EEG and HRV to monitor industrial workers' stress levels continuously raises notable ethical concerns. Concerns for privacy, consent, data usage, data ownership, and mental infrastructure are at stake. There are critical boundaries involving workers' data and professional risks which must be safeguarded. Additionally, withdrawing from participation and maintaining professional autonomy without repercussions must be possible. Basic algorithms to remove, encrypt, and restrict access to personal data greatly assist in data safety. Algorithms also need to guarantee fairness. Stress predicting algorithms must not be employed for discriminatory practices like biased hiring, evaluation, or even task assignments.

Training data biased on age, gender, or even neurological divergence is capable of perpetuating biased evaluations for measuring performance. Next-gen algorithms for measuring cognitive performance need to cross-audit biases and include diverse datasets to eliminate the potential of exclusion. This part highlights the next-gen cognitive sensing platform integrating AR, contextual baselining, and federated machine learning. Such advancements are expected to improve intrusiveness, personalization, and scalability. Technological advancements require balance. This balance must uphold ethical parameters to sustain human dignity alongside technological efficiency. Innovation without trust, inclusiveness, and transparency lacks the infrastructure to support cognitive monitoring technologies for 5.0 industrial workplaces.

6.1 Bias, Privacy, and Algorithmic Governance

Carefully governed biometric monitoring systems have the potential to introduce or reinforce existing biases. Any algorithmic governance based on stress data needs to be explicable, justifiable, and accountable. Mitigating algorithmic exclusion challenges within biases can be addressed by training models on more heuristic populations and by engaging interdisciplinary ethics boards. Especially within work settings, consent must be revocable, non-coercive, and informed. In addition to the above, data can be safeguarded and kept transparent through privacy-enhancing technologies such as anonymized data pipelines, blockchain-backed access logs, and federated analytics. Ethical boundaries must be observed in the cognitive sensing technology: deployment must balance productivity and workforce control vis a vis technician autonomy, equity, and psychological safety in the long-term.

7. CONCLUSION

Wearable biosensors allow for real-time stress detection in PLC technicians. An automated control task in real-world frameworks was used to conduct the experiment in the study. EEG, HRV, and GSR measures were monitored and detected both workloads and stress during the different levels of workloads. With the aid of subjective experience ratings, stress classification for technicians proved to be highly accurate, affirming the hypotheses on stress detection.

The insight received enhances the possibility of integrating cognitive consideration into feedback mechanisms for industrial control systems in the PLC for adaptive and personalized automated assistance. This leads to deterred operational error, improved safety, and improved technician health and retention—all contributing to the reduction of unnecessary expenditures in the organization. Despite the observed benefits, the study also outlines ethical concerns that emerge for PLC systems that employ monitoring systems with regards to privacy, fairness, and worker autonomy. Research in this area should work towards creating algorithms that increase inclusiveness and allow for real-time feedback, as well as focus on long-term monitoring. While the PLC system aims to streamline processes and increase efficiency, automation focused on stress detection provide an opportunity to integrate productivity with mental well-being, fostering a psychologically safe environment. When coupled with human-centered design, automation technologies in workplaces shift from mechanical to nurturing. This will facilitate enduring integration of humans and machines in Industry 5.0.

REFERENCE

1. Matkarimov, I., Sallaah, M.H, Salayev, U., Kumar, S., Khaitova, D., & Udayakumar, R. (2025). Climate-induced stress and disease dynamics in aquaculture species. International Journal of Aquatic Research and Environmental Studies, 5(1), 1–11. https://doi.org/10.70102/IJARES/V5S1/5-S1-01
2. Raman, A., Ting, N. W. Y., Balakrishnan, R., Sanjeevi, B., & Arumugam, V. (2024). Intelligent Resource Monitoring and Control Method in Vehicular Ad-hoc Networks for Electric Vehicle Enabled Microgrids. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 15(3), 50-59. https://doi.org/10.58346/JOWUA.2024.I3.004
3. Boopathy, E. V., Shanmugasundaram, M., Vadivu, N. S., Karthikkumar, S., Diban, R., Hariharan, P., & Madhan, A. (2024). Lorawan based coalminers rescue and health monitoring system using Iot. Archives for Technical Sciences, 2(31), 213–219. https://doi.org/10.70102/afts.2024.1631.213
4. Guru Prasad, S., & Badrinarayanan, M. K. (2025). A Study on the Adoption of Threat Prevention and Dark Web Monitoring for Information Security Management in India. Indian Journal of Information Sources and Services, 15(2), 154–159. https://doi.org/10.51983/ijiss-2025.IJISS.15.2.21
5. Salave, A. P. (2025). Cloud-edge hybrid deep learning framework for real-time traffic management. Electronics, Communications, and Computing Summit, 3(2), 28–39.
6. Tandi, M. R. (2024). 6G terahertz communication: Key challenges, enabling technologies, and future directions. Electronics, Communications, and Computing Summit, 2(2), 44–50.
7. Karimov, Z., & Bobur, R. (2024). Development of a Food Safety Monitoring System Using IOT Sensors and Data Analytics. Clinical Journal for Medicine, Health and Pharmacy, 2(1), 19-29.
8. Arvinth, N. (2025). Effect of Pranayama on respiratory efficiency and stress levels in adolescent athletes. Journal of Yoga, Sports, and Health Sciences, 1(1), 1–8.

9. Yadav, A., & Yadav, P. (2014). Role of Gender: Information Technology and Organisational Stress. International Academic Journal of Organizational Behavior and Human Resource Management, 1(2), 34–46.
10. Anusuya, J. (2024). Subjugation of Indian Women in Anita Nair's Ladies Coupe. International Academic Journal of Social Sciences, 11(1), 39–42. https://doi.org/10.9756/IAJSS/V11I1/IAJSS1105
11. Menaka, S. R., Gokul Raj, M., Elakiya Selvan, P., Tharani Kumar, G., & Yashika, M. (2022). A Sensor based Data Analytics for Patient Monitoring Using Data Mining. International Academic Journal of Innovative Research, 9(1), 28–36. https://doi.org/10.9756/IAJIR/V9I1/IAJIR0905
12. Idris, I., Nasir, M., Hersogondo, H., & Situmorang, T. (2025). Intergeneration Relationship Quality and Family-Firm Sustainability. Quality-Access to Success, 26(205).
13. Al-fulayih, R. Z. A., Burjes, A. Y., & Ghadeer, E. E. (2023). Study the Stress Analysis of a Rectangular Plate with a Central Cut for Different Mesh by Ansys. International Academic Journal of Science and Engineering, 10(2), 169–175. https://doi.org/10.9756/IAJSE/V10I2/IAJSE1021
14. Bianchi, G. F. (2025). Smart sensors for biomedical applications: Design and testing using VLSI technologies. Journal of Integrated VLSI, Embedded and Computing Technologies, 2(1), 53–61. https://doi.org/10.31838/JIVCT/02.01.07
15. Iyer, D., & Nambiar, R. (2024). Marketing Innovations in the Digital Era: A Study within the Periodic Series of Multidisciplinary Perspectives. In Digital Marketing Innovations (pp. 12-17). Periodic Series in Multidisciplinary Studies.
16. Dimitriou, E., & Georgiou, A. (2025). Automatic Inspection Systems Cut Quality Control Costs by 60%. National Journal of Quality, Innovation, and Business Excellence, 2(1), 23-33.
17. Hussain, I., & Qureshi, A. (2024). Gender-Inclusive Energy Transitions: Empowering Women in Renewable Energy Sectors. International Journal of SDG's Prospects and Breakthroughs, 2(2), 7-9.
18. Rathore, N., & Shaikh, A. (2023). Urbanization and Fertility Transitions: A Comparative Study of Emerging Economies. Progression Journal of Human Demography and Anthropology, 1(1), 17-20.