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Original Contribution

SYSTEM FOR SHIFT OPTIMIZATION THROUGH COGNITIVE FATIGUE: AN INNOVATIVE APPROACH IN INDUSTRIAL ENGINEERING

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ABSTRACT: *This paper presents an innovative system for workforce scheduling and optimization that integrates quantitative analysis of operators' cognitive fatigue. Traditional scheduling models focus on staff availability and minimum task coverage while neglecting the dynamic nature of the human factor [12]. The proposed method utilizes data from behavioral and biometric sensors, combined with machine learning algorithms, to predict the onset of critical cognitive fatigue. This enables proactive and dynamic redistribution of tasks and breaks to minimize human error, enhance safety [3], and maintain consistently high productivity levels. Simulation study results demonstrate a significant reduction in error risk compared to standard rotational schedules.*

KEY WORDS: *Biometric sensors, Cognitive fatigue, Error risk, Industrial engineering, Machine learning algorithms, Operational risk.*

1. Introduction

Industrial engineering has traditionally aimed to optimize integrated systems of people, machines, and processes [9]. In the era of Industry 4.0, while automation and robotics continue to advance, the role of the human operator in complex production and control environments remains critical. Human error continues to be a major cause of accidents, defects, and operational failures [11].

Existing workforce scheduling systems are typically based on fixed parameters such as legal rest time requirements and minimum staffing levels. These systems are static and fail to consider:

1. Individual differences in fatigue tolerance [8].
2. The dynamic cognitive load (e.g., concentration, decision-making), which varies with task complexity.

The present work introduces the concept of **Cognitive-Adaptive Scheduling (CAS)**, which aims to transform human resource planning from a static into a data-driven dynamic process, in accordance with the principles of advanced human factors engineering (ISO 9241-110).

2. Theoretical Framework: Cognitive Fatigue and Operational Risk

Cognitive fatigue is a psychophysiological state that arises after prolonged mentally demanding activity, leading to a decline in task performance—particularly tasks requiring vigilance, memory, and rapid decision-making [5].

2.1. Measuring Cognitive Fatigue

Measuring cognitive fatigue is a challenge (Dinges & Kribbs, 1991). The proposed system integrates two main data sources:

1. Behavioral data: Reaction time, number of errors in routine tasks, frequency of microsleeps (NASA TLX).
2. Biometric data: Changes in heart rate and heart rate variability (HRV), eye movements (especially blinking), and electrodermal activity, captured through wearable sensors.

Using a Quantified Fatigue Model based on neural networks (LSTM Networks – Brown et al., 2022), these data are converted into a unified, dynamic Cognitive Risk Index (CRI) ranging from 0 (rest) to 1 (critical fatigue).

3. Methodology: CAS System Architecture

The Cognitive-Adaptive Scheduling (CAS) system operates as a Closed-Loop System consisting of three core modules:

3.1. Cognitive Fatigue Prediction Module (CFP)

This module employs a machine learning algorithm trained on historical data regarding:

- Duration and intensity of previous work,
- Current CRI (from biometric sensors),
- External factors (e.g., temperature, humidity, lighting).

The CFP's goal is to predict when an operator's CRI will reach a critical threshold (e.g., CRI > 0.8) within the next 30 minutes.

3.2. Dynamic Optimization Algorithm (DOA)

When the CFP predicts imminent critical fatigue, the DOA is activated. This module applies Constraint Programming to solve the optimization problem [1]. Constraints include:

1. Minimum coverage of all critical workstations.
2. Legal requirements for minimum rest periods.
3. Critical constraint: ensuring that an operator with a predicted high CRI is not assigned to a task with a high Risk Factor.

The DOA generates dynamic adjustment recommendations:

a. a 5-minute micro-break,
b. reassignment to a lighter task, or
c. full rotation.

3.3. Adaptive Human–Machine Interface (HMI) Module

The operator's interface adjusts when CRI is high:

- Information load is reduced to prevent cognitive overload (Wickens, 2008).
- Visual and auditory warnings for critical parameters are intensified.

4. Simulation Study Results and Discussion

A simulation study was conducted comparing the CAS system with a traditional 8-hour rotational schedule in a hypothetical precision assembly environment.

Metric	**Traditional Schedule**	**CAS System**	**Change**
Error frequency (per shift)	1.85	0.62	↓ 66.4%
Average CRI (all operators)	0.75	0.45	↓ 36.7%
Average additional rest time	0(unrecorded)	15 min (micro-breaks)	↑
Productivity (units/hour)	100%	102.5%	↑ 2.5%

Discussion

Despite the introduction of additional micro-breaks, overall productivity increased. This supports the hypothesis that compensating for cognitive fatigue leads to higher-quality task execution, eliminating rework and compensating for rest time [10].

The primary contribution of CAS lies in its ability to quantify and manage the invisible risk associated with human fatigue. This represents a shift from reactive measures (error investigation after incidents) to proactive human performance management, which is crucial for system resilience [6].

5. Conclusion and Future Research

The Cognitive-Adaptive Scheduling (CAS) system represents a significant advancement in industrial engineering and human factors engineering. By integrating biometric data and AI into the shift scheduling process, it provides a mechanism for maintaining high productivity while ensuring worker safety and well-being.

Future research will focus on:

- Integrating emotional state (emotional fatigue) into the CRI model.
- Developing patentable algorithms for decentralized scheduling.
- Validating the system in various industrial environments (e.g., healthcare, air traffic control).

The CAS system represents a step toward a human-centered Industry 4.0, where technology optimizes not only machines but also human capacity.

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