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AI- Driven Ergonomic Optimization Framework for FDM-Based 3D printing Environments

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***Abstract* - This study presents an AI-driven ergonomic optimization framework for Fused Deposition Modelling (FDM)-based 3D printing environments. The research investigates the relationship between process parameters, operator posture, monitoring frequency, and fatigue level during additive manufacturing operations. Experimental observations were conducted using a Creality K1 FDM printer with PLA material at different print speeds of 40 mm/s, 80 mm/s, and 120 mm/s. The results indicate that lower print speeds increase operator workload due to prolonged monitoring requirements and exposure to static postures. The proposed framework integrates Artificial Intelligence, sensor systems, and ergonomic assessment principles to enable real-time monitoring and adaptive decision-making. The framework supports future Industry 4.0 manufacturing environments by improving operator safety, reducing fatigue, and enhancing productivity. The study highlights the importance of combining human-centered ergonomics with intelligent manufacturing technologies for sustainable additive manufacturing systems**.

***Index Terms* - Additive Manufacturing, Ergonomics, Artificial Intelligence, FDM, Industry 4.0, Operator Fatigue**

I. INTRODUCTION

Additive Manufacturing (AM), commonly known as 3D printing, has emerged as one of the most transformative technologies in modern manufacturing industries due to its ability to fabricate complex geometries directly from digital models with reduced material waste and shorter production cycles [1]. Among various additive manufacturing techniques, Fused Deposition Modelling (FDM) is widely adopted because of its affordability, simplicity, and accessibility in educational, industrial, and research applications [2]. The increasing utilization of FDM technology across multiple sectors has significantly improved rapid prototyping, customized manufacturing, biomedical applications, and small-scale industrial production

Despite these advantages, FDM printing operations still depend heavily on continuous human involvement during machine setup, filament loading, bed levelling, parameter adjustment, and print monitoring [3]. These repetitive tasks often require prolonged sitting or standing postures, repetitive hand movements, and continuous visual attention, which may contribute to physical discomfort, musculoskeletal disorders, and cognitive fatigue among operators [4]. Previous ergonomic studies have shown that improper workstation conditions and repetitive occupational activities can negatively influence operator health, productivity, and workplace efficiency [5].

In addition to physical ergonomic challenges, cognitive workload has become an important concern in additive manufacturing environments. Operators are frequently required to monitor print quality, detect process failures, and make immediate decisions during long-duration printing operations. In multi-printer manufacturing setups, the cognitive demands increase further due to simultaneous supervision of multiple machines [6]. Environmental conditions such as poor lighting, elevated temperature, continuous machine noise, and exposure to ultrafine particle emissions from FDM printers may also influence operator safety and comfort [7].

Traditional ergonomic assessment methods such as Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) are commonly used to evaluate ergonomic risks in industrial environments [8], [9]. However, these methods are generally observation-based and lack real-time adaptability for dynamic manufacturing systems. The integration of Artificial Intelligence (AI), machine learning, computer vision, and sensor technologies offers significant opportunities for continuous ergonomic monitoring and intelligent decision-making in modern manufacturing environments [10].Recent developments in AI-based posture recognition and human activity analysis have demonstrated the effectiveness of deep learning algorithms such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks in ergonomic monitoring applications [11]. These technologies enable real-time posture analysis, fatigue prediction, and adaptive ergonomic interventions, thereby supporting safer and more efficient human-machine interaction systems.Although AI-assisted ergonomic systems have been explored in sectors such as healthcare, automotive assembly, and industrial automation, limited research has specifically focused on ergonomic optimization in FDM-based additive manufacturing environments [12]. Therefore, this study proposes an AI-driven ergonomic optimization framework for FDM 3D printing systems to analyse the relationship between process parameters, monitoring frequency, operator posture, and fatigue levels. The proposed framework integrates ergonomic assessment principles with AI-based monitoring techniques to support future Industry 4.0 smart manufacturing environments.

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II. LITERATURE REVIEW

A. Ergonomics in Manufacturing Systems

Ergonomics is an interdisciplinary field focused on optimizing human well-being, safety, and system performance within working environments [13]. In manufacturing industries, ergonomic principles are widely applied to reduce physical strain, minimize workplace injuries, and improve operational efficiency. Traditional ergonomic assessment methods such as Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), and Ovako Working Posture Analysis System (OWAS) are commonly used to evaluate posture-related musculoskeletal risks in industrial workstations [8], [9].

Previous studies have shown that repetitive movements, awkward postures, and prolonged exposure to static positions significantly contribute to musculoskeletal disorders among industrial workers [14]. In addition, workplace environmental factors including lighting, temperature, vibration, and noise influence operator comfort, cognitive performance, and fatigue levels [15]. These findings highlight the importance of integrating physical, cognitive, and environmental ergonomic considerations into modern manufacturing systems.

B. Ergonomic Challenges in Additive Manufacturing

Additive Manufacturing (AM), particularly Fused Deposition Modelling (FDM), has gained widespread attention because of its flexibility, rapid prototyping capability, and cost-effective production processes [1]. Despite its technological advantages, FDM operations still require substantial human interaction during printer setup, parameter adjustment, print supervision, and post-processing activities.

Several studies have identified ergonomic risks associated with 3D printing operations. Dempsey et al. reported that a large percentage of 3D printing operators experience discomfort in the neck, shoulder, and upper limb regions due to repetitive monitoring activities and prolonged workstation exposure [3]. Bjornsson and Thorvaldsdottir conducted electromyography (EMG)-based analysis during FDM operations and observed continuous trapezius muscle activation beyond recommended ergonomic thresholds [6].

Environmental health concerns in additive manufacturing have also been widely investigated. Stephens et al. demonstrated that desktop FDM printers emit ultrafine particles and volatile organic compounds during printing processes, potentially affecting indoor air quality and operator respiratory health [7]. Similarly, Kim et al. reported that prolonged exposure to emissions generated during thermoplastic extrusion may influence workplace safety and environmental comfort [16].

In addition to physical ergonomic challenges, cognitive workload has become an important concern in multi-printer manufacturing environments. Continuous print monitoring, fault detection, and rapid decision-making can increase mental fatigue and reduce operator efficiency during long-duration printing operations [11].

C. Artificial Intelligence in Ergonomic Monitoring

The integration of Artificial Intelligence (AI) into ergonomic systems has significantly improved real-time monitoring, posture analysis, and fatigue prediction capabilities in industrial applications [12]. Unlike conventional observational assessment methods, AI-assisted ergonomic systems can continuously analyse operator movements, environmental conditions, and physiological responses using computer vision, wearable sensors, and machine learning algorithms.

Deep learning techniques such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have demonstrated high accuracy in human activity recognition and posture classification tasks [10]. These models can process time-series sensor data and identify ergonomic risk patterns associated with repetitive tasks and improper postures.

Plantard et al. proposed a Kinect-based ergonomic assessment system capable of real-time posture tracking and movement analysis in industrial work environments [11]. Similarly, Vignais et al. developed an AI-assisted feedback framework that provides corrective ergonomic recommendations during occupational tasks [12]. Recent transformer-based posture recognition systems have further improved ergonomic monitoring accuracy and adaptive intervention capabilities [10]

D. Research Gap

Although previous studies have explored ergonomic assessment methods and AI-based monitoring systems, limited research specifically addresses ergonomic optimization in FDM-based additive manufacturing environments. Most existing ergonomic studies focus primarily on automotive assembly lines, healthcare systems, and general industrial operations rather than 3D printing applications.

Current research also lacks comprehensive frameworks that integrate physical posture analysis, environmental monitoring, cognitive workload assessment, and AI-assisted decision-making within a unified additive manufacturing environment. Furthermore, real-time adaptive ergonomic intervention systems for FDM printing operations remain largely unexplored.

III. OBJECTIVES OF THE STUDY

The primary objective of this study is to develop an AI-driven ergonomic optimization framework for Fused

Deposition Modelling (FDM)-based additive manufacturing environments. The research focuses on analysing the relationship between process parameters, monitoring frequency, operator posture, and fatigue levels during 3D printing operations.

The specific objectives of the study are as follows:

1. To analyse ergonomic challenges associated with FDM-based 3D printing operations.
2. To investigate the influence of print speed on operator workload and fatigue level.
3. To evaluate the relationship between monitoring frequency, posture behaviour, and ergonomic strain.
4. To study the impact of environmental conditions on operator comfort and cognitive workload.

IV. METHODOLOGY

This study adopts an observation-based experimental methodology to investigate ergonomic challenges in FDM-based additive manufacturing environments and to develop an AI-driven ergonomic optimization framework.

The overall research workflow consists of five major stages:

- Experimental setup preparation
- Operator activity observation
- Ergonomic data collection
- Statistical analysis
- AI-based framework development

Experimental Setup

The experimental study was conducted using a Creality K1 FDM 3D printer under controlled laboratory conditions. Polylactic Acid (PLA) filament was selected as the printing material because of its widespread use and stable printing characteristics.

Parameter	Specification
Printer	Creality K1
Technology	FDM
Material	PLA
Print Speeds	40, 80, 120 mm/s
Environment	Indoor laboratory

Data Collection Procedure

During each printing cycle, operator activities were continuously observed and recorded. The operator performed standard FDM operational tasks including machine monitoring, print quality inspection, filament handling, and workstation interaction.

The following ergonomic parameters were observed:

- Monitoring frequency
- Sitting duration
- Standing duration
- Operator posture
- Fatigue level
- Environmental condition

D. AI-Based Ergonomic Framework

The proposed AI-driven ergonomic framework consists of three primary layers:

1. Data acquisition layer
2. Processing layer
3. Decision-support layer

The processing layer utilizes Artificial Intelligence and machine learning algorithms for ergonomic analysis. Convolutional Neural Networks (CNNs) can be employed for posture recognition and movement classification, while Long Short-Term Memory (LSTM) networks can analyse time-series ergonomic data to identify fatigue-related patterns.

V. RESULTS AND DISCUSSION

A. Relationship Between Print Speed and Operator

Fatigue The experimental observations revealed a significant relationship between print speed, monitoring frequency, and operator fatigue in FDM-based additive manufacturing environments. At lower print speeds (40 mm/s), the printing duration increased considerably, requiring prolonged monitoring and continuous operator attention throughout the printing process. This contributed to increased physical strain and cognitive fatigue. At higher print speeds (120 mm/s), the total printing duration decreased significantly, thereby reducing operator monitoring frequency and exposure time. This resulted in lower ergonomic workload and improved operator comfort.

B. Statistical Analysis of Ergonomic Parameters

TABLE II. Ergonomic Observation Data

Print Speed (mm/s)	Monitoring Count	Sitting Time (min)	Standing Time (min)	Fatigue Level
40	6	45	15	7
80	10	35	25	5
120	15	25	35	3

The results indicate that prolonged exposure to monitoring tasks and static postures significantly contributes to ergonomic fatigue during low-speed printing operations.

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C. Environmental Influence

Environmental conditions such as lighting, room temperature, ventilation, and machine-generated noise were observed to influence ergonomic outcomes during FDM operations.

Poor lighting conditions increased visual strain during detailed print inspection tasks. Continuous operational noise contributed to mental fatigue during prolonged operation periods.

D. AI-Driven Ergonomic Optimization

The observed experimental trends provide a strong foundation for the development of AI-assisted ergonomic monitoring systems in additive manufacturing environments.

Artificial Intelligence-based systems can continuously analyse operator posture, workstation interaction, and environmental conditions in real time using computer vision systems and sensor integration. CNNs and LSTM models can identify fatigue-related patterns and generate adaptive ergonomic recommendations.

VI. CONCLUSION

This study presents an AI-driven ergonomic optimization framework for Fused Deposition Modelling (FDM)-based additive manufacturing environments. Experimental observations demonstrated a strong relationship between process parameters, monitoring frequency, operator posture, and fatigue levels during 3D printing operations.

The results showed that lower print speeds significantly increase operator workload due to prolonged monitoring duration and extended exposure to static postures. Environmental conditions such as lighting, ventilation, and machine-generated noise were also found to influence ergonomic performance.

The proposed AI-based framework integrates Artificial Intelligence, machine learning, computer vision, and sensor technologies to support real-time ergonomic monitoring and adaptive decision-making. The framework provides a strong foundation for future research involving wearable sensors, predictive fatigue analysis, and intelligent workstation optimization in additive manufacturing industries.

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