To Enhance the Productivity of Machine and Labor with AI in Furnace Manufacturing Industry

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Abstract: ***We observed many problems in the furnace manufacturing especially in the fabrication process while studying the workers' pattern and their traditional working experience is not helpful in future growth so it leads to loss of jobs and wastage of time and resources. We applied the industrial engineering tools to improve the productivity of labour with the help of AI integrated with AR and VR for better understanding the real world problem. While implementing the hybrid concepts the workers understood the process and analysed the problem into the real world and it reduces the stress, traditional process and also improves the machining process and tool life.***

Keywords: Artificial Intelligence, Virtual Reality in Industry, Augmented Reality in Industry

1. Introduction

Time is money. In this rivalry and smart era. Resources are scarce and consumer demands are unlimited. The industry can't afford wastage of time and resources. Due to lack of skilled workers and lack of job opportunities. It is challenging for an organization to retain skilled workforce because of many parameters such as ergonomics, social security and workers safety. So AI plays a crucial role in training, upskilling and better understanding of services. Some reports show that AI will replace human roles in industry. When a new employee joins an organization the freshers do not have much practical experience in the organization and experts are also occupied in the other roles and responsibilities so AI plays a crucial role in training and development of freshers. AI is accountable for technical accuracy and performance. The AI integrates with Augmented Reality and Virtual Reality to help workers to improve their productivity.

The simulations training program is designed to help the new employees to understand each component's functions and its role from scratch. Augmented Reality helps workers how to assemble the components, which tools are required for dimensions of components, how to complete the circuits, and cross check the assembled product and save the time in quality check control departments. Artificial Intelligence integrates with Mixed Reality and also helps to identify the problems faced by consumers. It improves the timely inspections and maintenance so that time loss and any other casualties can be prevented. AR also makes sure that no workers waste any material in industry. When Mixed Reality is integrated with AI it also shows the best possible alternative and cost effective approach without compromising the quality standard of products and services. The setup cost of advanced manufacturing systems is comparatively higher compared to giving training to workers. Also Advanced Manufacturing Systems are frequently targeted by cyber attacks i. e, maintenance cost for advanced manufacturing systems is high for small, medium enterprises .

Augmented Reality highlights 24 percent of the Virtual world and 76 percent of real world. It superimposes the digital image or animation into the physical world by creating a new interactive experience. AR helps the workers to analyze the potential problems of the real world. For example if an equipment is not functioning correctly then AR help assistance integrate with AI guides the self service to solve the problems and complete the AR self diagnosis process. It reduces the shutdown time in industries. There are other expensive options to improve the productivity of workers but AR and VR is economical for micro, small, medium enterprises. AR also reduces the language barriers and it allows even migrants to understand the technical aspects of products in their native languages. Additionally Mixed reality shows that decision - making processes also improved by integrating with AI. High setup cost of advanced manufacturing systems is unbearable for a manufacturing industry so that they do not require workers if they set up advanced manufacturing systems. This leads to job loss and creates a vacuum in the society. Manufacturing cost is also high with advanced systems and it leads to inflation and recession. Small frontier firms experience a higher labour productivity growth through AI integration [1].

Artificial intelligence is set to revolutionize the manufacturing sector by reshaping key aspects of production. This transformation will be fueled by advanced technologies aimed at improving: (1) the design and planning of production systems, (2) process modeling, management, and optimization, (3) quality control and maintenance, and (4) automated assembly and disassembly. Practical applications of AI in this field include utilizing computer vision to automate machining operations, leveraging natural language processing to optimize maintenance processes, and applying human action recognition for enhanced process monitoring and inspection [2].

To address challenges such as limited interpretability and performance decline in data - scarce environments—factors that restrict AI's widespread adoption in industries—various deep learning subfields are being actively explored. These include physics - informed deep learning, explainable AI, domain adaptation, active learning, multi - task learning, and graph neural networks. Additionally, the integration of AI with other engineering disciplines holds significant potential and should not be underestimated [3]. The proposed architectural framework is founded on three core technical pillars: (1) enhancing the capabilities of existing layers within the Reference Architectural Model for Industry 4.0, (2) introducing new layers to support collaboration through human - in - the - loop approaches and

federated systems, and (3) addressing security challenges using AI - driven mechanisms. Furthermore, an analysis of industrial applications—focused on optimizing manufacturing logistics and enabling zero - defect production—demonstrates the practical viability of these architectural components [4]. The framework aims to deliver a comprehensive educational experience through an interactive VR environment, incorporating three key components: (1) Robotic platform system design and modeling, allowing users to engage in the design and simulation of robotic platforms under diverse conditions; (2) A virtual manufacturing company, providing a detailed digital representation of a manufacturing environment to deepen users' understanding of manufacturing systems and enhance problem - solving skills in realistic scenarios; and (3) Product evaluation, enabling users to utilize VR for thorough assessment of robotic platforms to ensure optimal performance and customer satisfaction [5].

The impact of Artificial Intelligence in industry is both transformational and disruptive, continuously reshaping industry standards and creating significant values [6]. The overall impact of AI adoption on enterprise labor demand remains minimal due to the balancing effects of substitution, complementarity, and job creation. As AI integration increases, businesses experience production scale expansion and higher labor productivity, leading to continuous improvements in workforce structure. However, this optimization may pose a potential risk of reduced overall labor demand. To mitigate AI's impact on employment, it is crucial to implement measures such as entrepreneurial guidance, policy support for displaced workers, skills training, and social security programs. These initiatives can help ease workforce transitions and enhance reemployment opportunities, ultimately strengthening job market competitiveness [7].

The advancement of industrial AI solutions focuses on: (i) facilitating the adaptation process, (ii) supporting solution engineering, (iii) enabling seamless integration into existing systems, (iv) ensuring safety compliance, and (v) fostering trust in industrial AI applications [8]. AI - driven data analytics and predictive analysis enhance economic efficiency and managerial practices in Industry 4.0 by providing real - time insights and trend forecasting. These technologies improve decision - making, risk management, and operational agility. However, challenges include limited adoption, data complexity, and historical biases. Environmental concerns, such as electronic waste disposal, also require attention. Addressing these issues can help businesses leverage AI for sustainable growth and competitive advantage [9]. The experimental results demonstrate the chatbot's effectiveness in extracting equipment statuses and predictive maintenance data using natural language. The system achieved 90.9% accuracy in retrieving troubleshooting information from 13 queries and 100% accuracy for predictive maintenance analysis. With an average response time of under 10 seconds, it significantly reduces the need for maintenance supervisors to conduct manual data analysis, thereby minimizing factory downtime. This customized chatbot integrates Industry 5.0 HMIs into Industry 4.0, enhancing interactive, personalized human - machine communication beyond traditional graphical interfaces. Additionally, the research supports manufacturing SMEs in adopting advanced technologies, helping them stay competitive in an evolving industrial landscape [10].

2. Methodology

1) Assess Current Productivity
2) Integrate AI for Machine Optimization
3) Improve Labor Efficiency with AI
4) Automate Routine Processes
5) Enhance Human - Machine Collaboration
6) Monitor Performance
7) Ensure Safety
8) Plot the observations on MATLAB software

3. Experimental Procedure

1) Compare the productivity of machines and labor in a fabrication process, with and without AI enhancements.
2) Specify the fabrication process (e. g., welding, assembly, cutting) and the type of AI enhancements (e. g., predictive maintenance, computer vision, process optimization).
3) Measure productivity metrics for human workers using traditional tools and methods.
4) Measure productivity metrics for machines operating without AI enhancements.
5) Measure productivity metrics for human workers using AI - assisted tools (e. g., augmented reality, AI - guided instructions).
6) Measure productivity metrics for machines with AI enhancements (e. g., IoT sensors, machine learning algorithms).
7) Observe and record output, quality, and downtime for human workers.
8) Collect data from machine logs, including output rates, downtime, and maintenance records.
9) Use sensors, wearables, or software to track worker performance with AI tools.
10) Gather data from AI systems, including predictive maintenance alerts, process optimization results, and real - time performance metrics.
11) Analyze Data to compare the metrics across the following categories, Output per unit time, Quality, Efficiency, Downtime
12) Evaluate AI Impact and how AI enhancements improve productivity of machine and labor
13) Draw Conclusions Identify which method (traditional labor, traditional machines, AI - enhanced labor, or AI - enhanced machines) is most productive for the specific fabrication process.

14) Prepare a detailed report summarizing the methodology, data, analysis, and conclusions also include visual aids (e. g., graphs, charts) to illustrate comparisons.
15) Plot the results on MATLAB Software for better visualization and comparison.

4. Results and Discussion

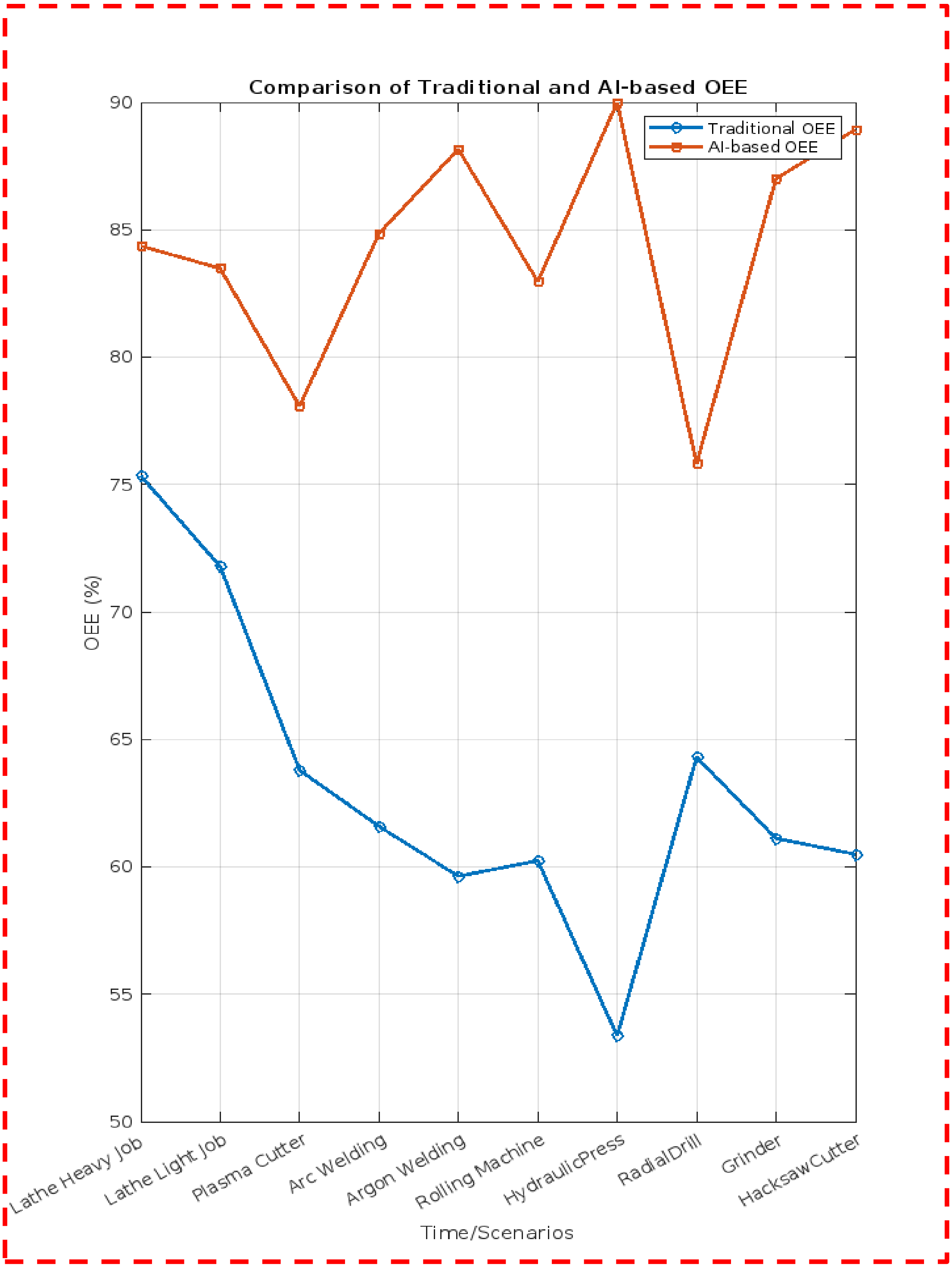

Figure 1: Comparison of Traditional and AI - based OEE

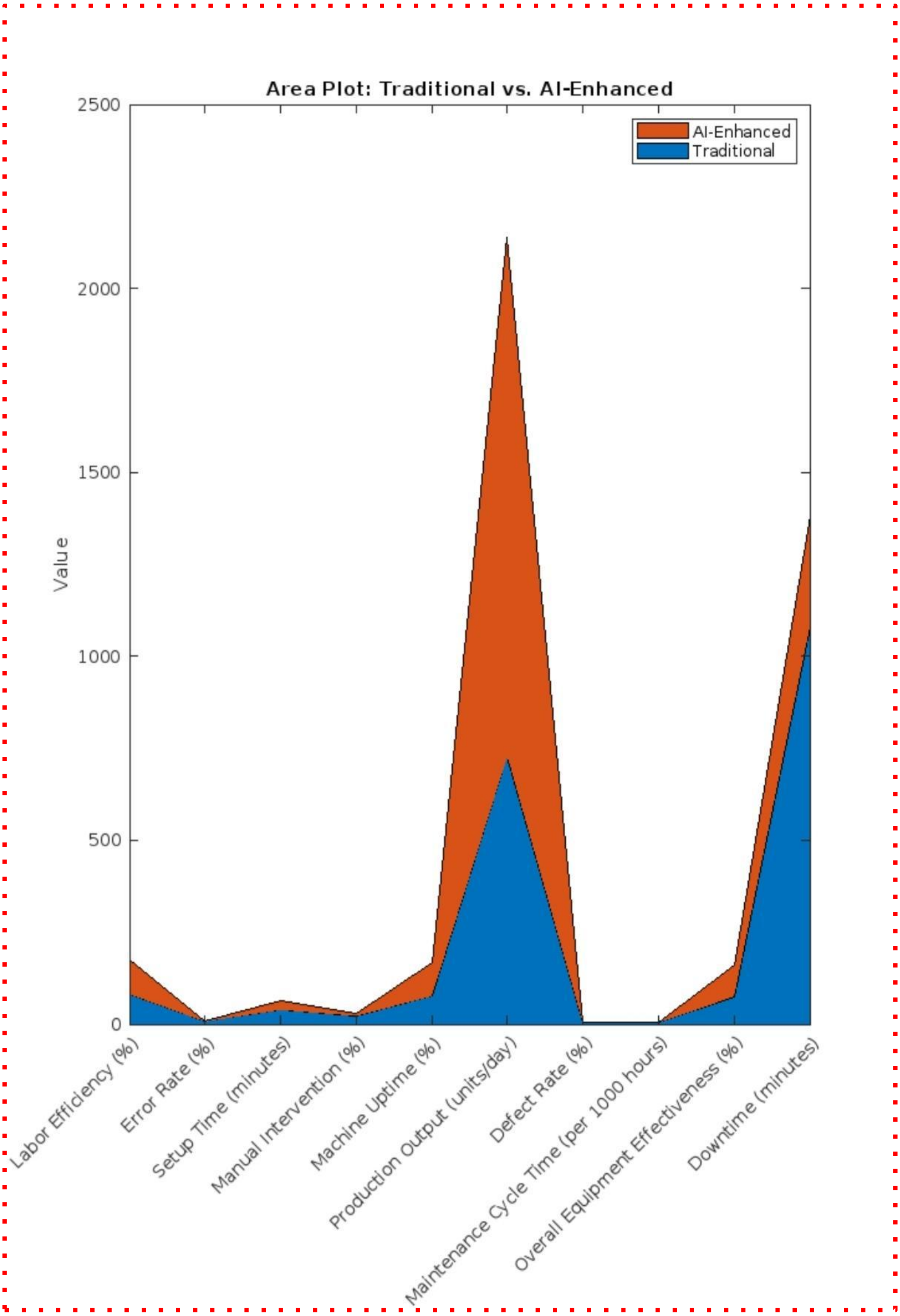

Figure 2: Traditional Vs AI - ENHANCED Parameters

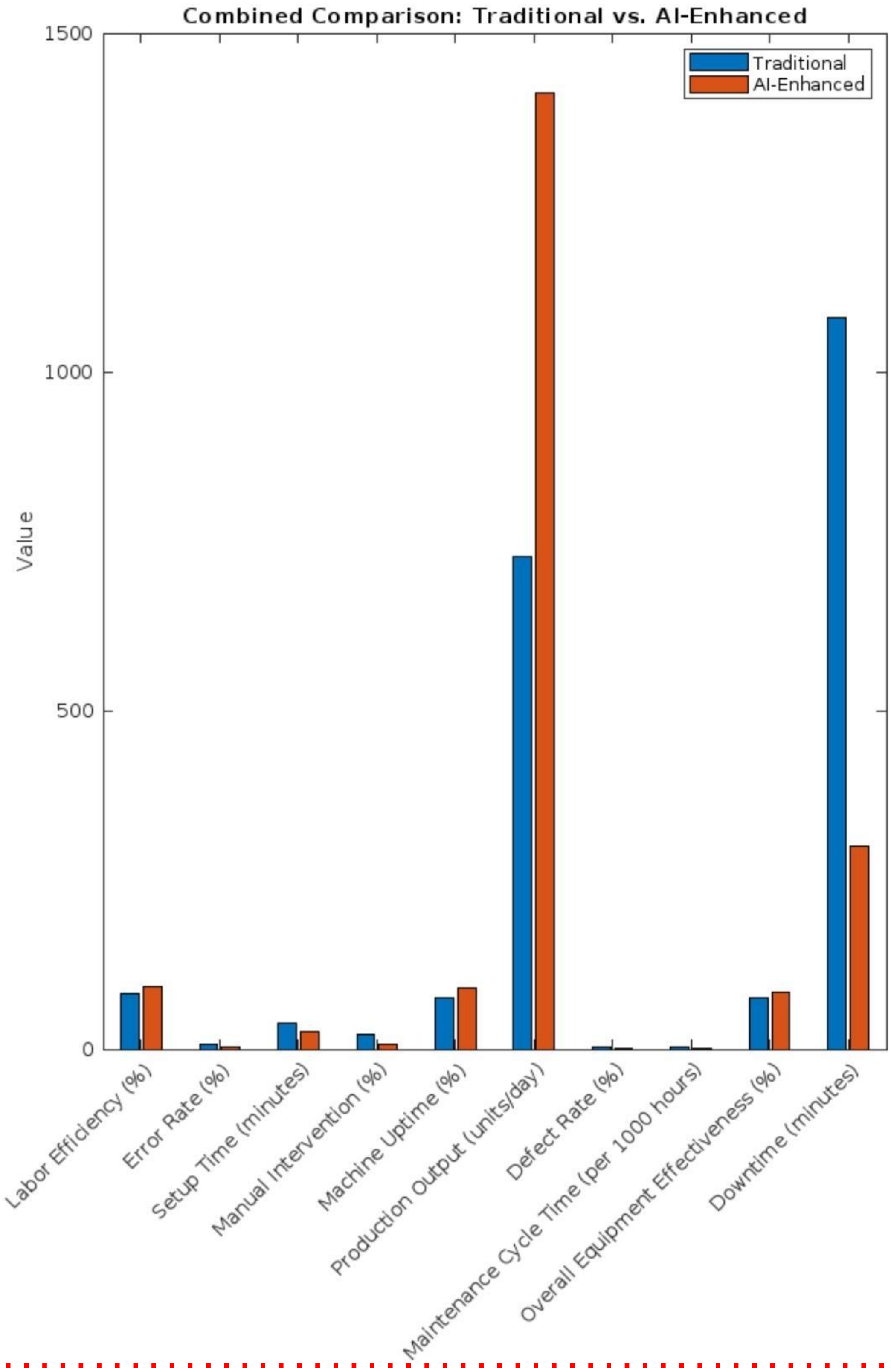

Figure 3: Combined Comparison of Labor and Machine Productivity with Traditional and AI - enhanced

Variable	Traditional	AI_Enhanced
{'Labor Efficiency (%)' }	81.6	92.33
{'Error Rate (%)' }	6.93	2.88
{'Setup Time (minutes)' }	39	26.2
{'Manual Intervention (%)' }	22.44	7.56
{'Machine Uptime (%)' }	76.31	90.13
{'Production Output (units/day)' }	728	1412
{'Defect Rate (%)' }	3.52	2.05
{'Maintenance Cycle Time (per 1000 hours)'}	3.92	2
{'Overall Equipment Effectiveness (%)' }	75.23	84.42
{'Downtime (minutes)' }	1080	300

Figure 4: Results showed that Traditional and AI Enhanced Parameters

The result provides a comparative analysis of traditional and AI - enhanced manufacturing processes, focusing on key performance indicators in fabrication. The results clearly demonstrate the advantages of AI - driven productivity enhancements across different parameters.

1) Labor Efficiency Improvement - AI - enhanced systems show a significant boost in labor efficiency, increasing from 81.6% to 92.33%. This suggests better resource utilization, reduced idle time, and optimized task allocation.
2) Reduction in Errors and Defect Rate - Error rates drop from 6.93 % to 2.88 %, while defect rates decrease from 3.52 % to 2.05 %. This improvement indicates better precision, likely due to AI - powered real - time quality monitoring and predictive adjustments.
3) Setup Time Optimization - The setup time is reduced from 39 minutes to 26.2 minutes, reflecting AI's role in streamlining preparatory work, automating adjustments, and reducing manual configurations.
4) Decreased Manual Intervention - AI - driven automation significantly reduces the need for manual intervention, dropping from 22.44 % to 7.56 %. This reduction enhances efficiency and minimizes human error.
5) Machine Uptime and Downtime Reduction - Machine uptime improves from 76.31% to 90.13%, while downtime drastically decreases from 1080 minutes to 300 minutes. This suggests effective AI - based predictive maintenance, which minimizes unexpected failures.
6) Production Output Doubling - The production output per day jumps from 728 units to 1412 units, illustrating the impact of AI - driven process optimizations and automation in achieving higher throughput.
7) Reduced Maintenance Cycle Time - AI - enhanced maintenance cycles show a decrease from 3.92 to 2 (per 1000 hours), indicating proactive maintenance strategies that prevent major breakdowns.
8) Overall Equipment Effectiveness (OEE) Enhancement - OEE improves from 75.23% to 84.42 %, which is a strong indicator of overall efficiency, encompassing availability, performance, and quality improvements.
9) The labor efficiency is increased by 13.1 % it shows that AI reduced workload inefficiencies, enabling workers to focus on high - value tasks. Increased automation enhances human productivity.
10) Error rate is reduced by 58.4% it shows the AI - driven quality control minimizes human errors, leading to fewer defective products and rework costs.
11) Setup Time is reduced by 32.8% it represents the ai optimizes workflow planning, reducing setup time and improving production readiness.
12) Manual intervention is decreased by 66.3% it shows that Ai handles routine adjustment, reducing reliance on human operators and lowering fatigue - related inefficiencies.
13) Machine uptime is increased by 18.1% and predictive maintenance ensures minimal unexpected failures, leading to higher operational availability.
14) Production output is increased with 94% shows optimized workflow and reduced idle time significantly boost production capacity
15) Defect rate reduced by 41.8% shows that Ai driven inspection detects defects earlier, improving product quality.
16) Maintenance cycle time os reduced by 49% it means ai driven predictive maintenance decreases unplanned repairs, reducing downtime and associated costs
17) Overall Equipment Effectiveness is increased by 12.2% it shows clearly that enhanced machine utilization, availability and efficiency directly boost OEE
18) Reduced Downtime by 72.2% indicated AI minimizes production interruptions and improving operational continuity

Hypothesis

"The integration of Artificial Intelligence (AI) with industrial engineering tools, such as Lean Manufacturing, Six Sigma, and Operations Research, will significantly enhance the productivity of both machines and labor in the furnace manufacturing industry. By leveraging AI for predictive maintenance, process optimization, and real - time data analytics, combined with industrial engineering methodologies for waste reduction and workflow efficiency, the overall operational performance will improve, leading to reduced downtime, lower costs, and higher output quality."

Key Components of the Hypothesis:

1) AI for Predictive Maintenance: AI algorithms will predict equipment failures, reducing unplanned downtime and improving machine reliability.

2) Process Optimization: AI will optimize furnace parameters (e. g., temperature, pressure) in real - time, while Lean Manufacturing tools will eliminate inefficiencies.
3) Workforce Productivity: AI - powered training and collaborative robots (cobots) will enhance labor efficiency, supported by ergonomic design principles.
4) Data - Driven Decision Making: AI will analyze production data, and Operations Research tools will optimize resource allocation and scheduling.
5) Quality Improvement: AI - driven quality control systems, combined with Six Sigma methodologies, will reduce defects and improve product consistency.

5. Conclusion

In conclusion, the comparative analysis highlights AI's transformative role in the fabrication process. The improvements in labor efficiency, reduced error rates, higher production output, and optimized maintenance cycles demonstrate the potential of AI - driven automation in boosting productivity and operational efficiency. As AI continues to evolve, its integration in manufacturing will likely lead to even greater advancements, reinforcing its value in industrial applications. The integration of Artificial Intelligence (AI) into the furnace manufacturing industry presents a transformative opportunity to enhance both machine efficiency and labor productivity. By leveraging AI - driven technologies such as predictive maintenance, real - time data analytics, and automated process optimization, manufacturers can significantly reduce downtime, minimize errors, and improve overall operational efficiency. AI - powered systems enable machines to operate at peak performance while providing workers with actionable insights and tools to streamline their tasks. This synergy between human expertise and intelligent automation not only boosts productivity but also fosters a safer and more innovative work environment. As the industry continues to evolve, embracing AI will be crucial for maintaining competitiveness, driving sustainable growth, and meeting the increasing demands of modern manufacturing. We obtained good results with proper training and techniques in furnace manufacturing industry

6. Future Directions

The integration of Artificial Intelligence with the help of AR and VR is a game changer in Furnace Manufacturing, Defense Industry, Automobile Industry, Aerospace Industry. AR and VR helps to optimize the utilization of resources and reduce the burden on workers. It also improves the training of workers to achieve their personal goals but also the goals of organization.

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