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Human-Centric IoT-Driven Digital Twins in Predictive Maintenance for Optimizing Industry 5.0

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***Abstract*— Predictive maintenance now heavily relies on digital twins and the Internet of Things (IoT), allowing industrial assets to be monitored and make real-time decisions. However, adding human components to conventional optimization processes creates new difficulties as Industry 5.0 moves toward human-centric systems. Existing frameworks frequently disregard human preferences, intuition, and safety considerations, which makes human operators distrustful and unwilling to accept them. This paper presents a novel multi-objective optimization framework to enable predictive maintenance that incorporates human feedback into IoT-driven digital twins. The framework uses an enhanced particle swarm optimization (PSO) algorithm to reconcile competing goals, including maintaining operator safety, optimizing asset reliability, and minimizing maintenance costs. Furthermore, maintenance tasks are adaptively scheduled using built-in reinforcement learning (RL), and optimized model parameters are fine-tuned to improve predictive accuracy using Bayesian optimization. The latter is based on real-time operational data. In addition to promoting a safer working environment, the suggested approach significantly reduces unplanned downtime and maintenance costs. This research contributes to developing more resilient, adaptive, and collaborative industrial systems by aligning with the human-centric principles of Industry 5.0. The proposed model was tested using the maintenance duration and improved 10 to 100 hours. The model was compared with the PSO algorithm, demonstrating its superiority with a 7.5% reduction in total maintenance cost and a 6.3% decrease in total downtime. These improvements enhance operational efficiency and better human-machine collaboration by minimizing unnecessary interventions and optimizing resource allocation.**

Keywords*— *Industry 5.0, Digital twin, IoT, Predictive maintenance, Enhanced PSO

I. INTRODUCTION

The integration of digital twin and Internet of Things (IoT) technologies into the industry makes a significant contribution to its innovation potential [1-4]. Digital twin technology is a real-time virtual representation of physical environments, which simulates industries' operations and optimizes companies' processes [5-8].

The continuous data flow from the sensors updates the historical data in operation. Compared to traditional methods, proactive and predictive maintenance approaches minimize operational interruptions in industries and extend equipment lifespan [9-12].

The advent of Industry 5.0 has shifted the focus towards a deeper collaboration between human intelligence and machine capabilities, moving beyond the automation-driven approach of Industry 4.0. This transition introduces new technological requirements, including the need for systems that prioritize human factors such as safety, satisfaction, and collaborative decision-making alongside technical efficiency [13, 14]. As such, Industry 5.0 calls for more advanced optimization frameworks that integrate human-machine synergy, allowing for more adaptable, context-aware systems in rapidly evolving environments. Compared to the old version, Industry 5.0 requires an advanced optimization approach that considers human and technical aspects to ensure performance and user-centricity. Despite the increasing importance of human-machine collaboration in existing predictive maintenance frameworks, human preferences, intuition, and real-time feedback are not sufficiently considered. This deficiency leads to wrong decisions, reduced trust in automated systems, and reduced adaptability in rapidly changing industrial environments [15-20].

This study proposes a framework to improve and optimize maintenance processes by considering the human factor using IoT-based digital twins. This method is established to solve the weaknesses in the current system to increase system and employee safety, reduce maintenance costs, and balance conflicting objectives. The algorithm provides a flexible optimization system that complies with Industry 5.0 standards and strengthens human-machine collaboration, enabling effective decision-making [21-26].

The proposed optimization offers three main contributions. The first is to interface humans with the machine, allowing humans to be integrated into the process. The second is to weight the parameters to minimize cost and time using the digital twin process. The third is introducing a framework to reduce maintenance costs, increase accuracy, and promote calibration between humans and the automated system.

This paper is organized as follows: Section 2 presents the related work. Section 3 provides the proposed system architecture and optimization methodology. Section 4 introduces the mathematical model and problem formulation. Section 5 gives the simulation setup and results. Section 6 concludes the research work.

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II. RELATED WORK

The predictive maintenance process became significant after IoT and digital twin technology were introduced. The main task in such an operation is to improve equipment reliability, allow data-driven decision-making, and enable real-time monitoring. The work in this paper investigates a research method for Industry 5.0 using optimization method, IoT, and digital twin for a successful predictive maintenance method. There are several research papers [27, 28] investigating the use of IoT to enable real-time data collection for industrial equipment. The latest research papers [29, 30] are considering machine learning methods to predict the failures of industrial systems. The paper in [31] presented a framework that combines machine learning with IoT-related data to forecast the lifespan of critical components. The studies indicate precise predictions by using IoT technology. The work in Industry 4.0 did not include the human factor in the operation. However, the upcoming Industry 5.0 requires the human factor to be essential to the operation to increase trust and cooperation. The operational accuracy of Industry 5.0 has further increased by applying digital twins.

The paper [32] introduces a digital twin operation that duplicates physical assets for major predictive maintenance. The advantage of this operation is that it allows real-time simulation and analysis for predictive maintenance. The paper also demonstrates the precision of decision-making stages. The paper [33] indicated that digital twins can lower the risk of failures for unplanned operations.

The studies are important to highlight the application of the digital twins, but human-centric factors and multi-objective optimizations are not considered in the process. The multi-objective optimization method is one of the suitable algorithms for predictive maintenance strategy. The paper [34] optimizes the maintenance schedule, considering reliability and cost factors. Furthermore, the paper [35] utilizes machine learning methods to modify maintenance in real-time based on the conditions of the equipment. Most research papers concentrate on technical performance majors without cooperating user references as needed in Industry 5.0.

The literature provides optimization methods for predictive maintenance. These methods include IoT and digital twins. The methods used today concentrate on cost and reliability factors, but little is known about dynamic, real-time optimization methods.

The proposed model presents an optimization framework using a multi-objective algorithm that considers the IoT-driven digital twins and humans in the mechanisms. The proposed model prioritizes safety and human concerns for predictive maintenance systems. This research aims to increase the flexibility and understandability of predictive maintenance approaches.

III. SYSTEM ARCHITECTURE

This section describes the methodology for combining advanced optimization methods and IoT digital twins into a maintenance framework for Industry 5.0. As shown in Figure I, the main difference between Industry 4.0 and Industry 5.0 is the human interaction, including resilience and sustainability.

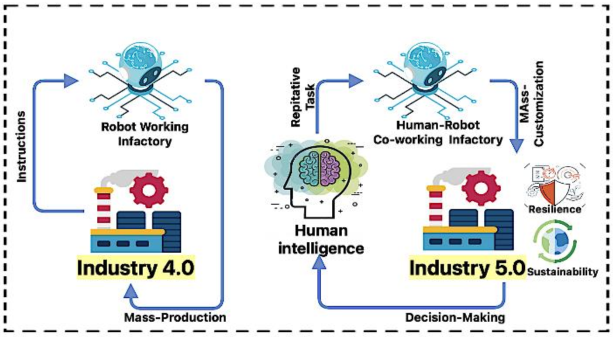

FIGURE I. ARCHITECTURE OF INDUSTRY 4.0 AND INDUSTRY 5.0

Figure I illustrate the transition from Industry 4.0, which focuses on automation and robotics, to Industry 5.0, which integrates human intelligence into production.

On the left side of the figure, Industry 4.0 is depicted with a robot-driven factory where robots receive instructions and perform mass production. The primary characteristic here is automation, with minimal human involvement.

In the center, human intelligence plays a crucial role in shifting from repetitive tasks to more complex decision-making.

On the right side of the figure, Industry 5.0 introduces human-robot collaboration, emphasizing mass customization rather than generic mass production. This approach enhances resilience and sustainability, as seen in the accompanying icons representing these principles.

The flow between the two paradigms highlights how industries are evolving to balance automation with human creativity and flexibility.

The work adopts a digital twin model that enables the analysis of the equipment's life cycle using real-time data sent from the sensors. Digital twin processing offers the advantage of simulating the behaviour and monitoring the maintenance procedure of the equipment and machinery in the production line. The main block of the digital twin architecture is shown in Figure II.

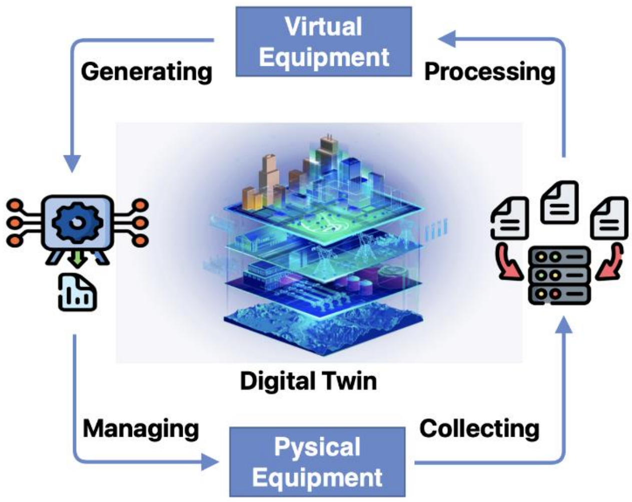

FIGURE II. DIGITAL TWIN STRUCTURE

The main parts of the framework consist of the IoT sensing layer, the digital twin layer, and the human interaction optimization layer to operate a maintenance prediction mechanism. The designed architecture provides real-time monitoring, a data-driven decision model, and human-machine interaction. Figure II illustrates physical and virtual equipment interaction through a digital twin.

At the bottom, physical equipment collects data through embedded sensors. The collected data moves to the processing stage, where a system interprets and stores it.

The processed data is used in the top section to generate a virtual representation of the equipment. The cycle is completed as the generated insights are used for managing physical equipment, enabling real-time monitoring, fault detection, and predictive maintenance.

The digital twin system creates a feedback loop, ensuring continuous optimization and improved efficiency.

The complete framework architecture was generated using ChatGPT and demonstrated in Figure III.

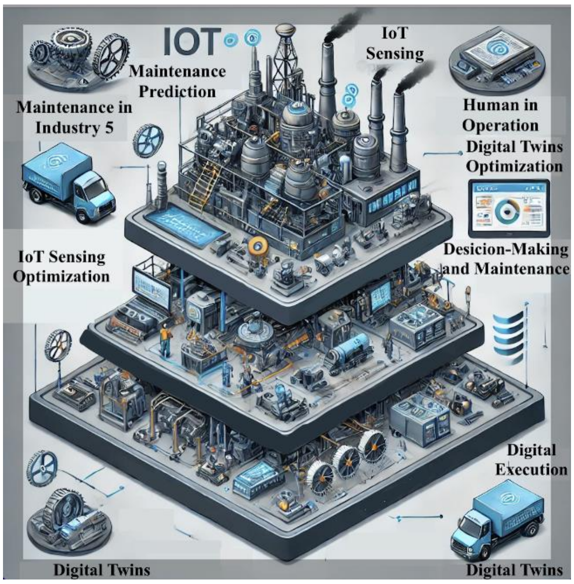

FIGURE III. FRAMEWORK ARCHITECTURE LAYERS

The main units consisting of the framework layers are described in the following subsections.

Figure III provides a multi-layered visualization of an advanced smart factory that integrates IoT sensors, Digital Twins, and AI-driven decision-making for optimized industrial operations.

The bottom layer represents Digital Twins, creating a virtual simulation of machinery and processes. The middle layer focuses on IoT sensing optimization, where interconnected devices collect real-time data. The top layer emphasizes decision-making and maintenance, where AI-driven analytics predict potential failures, ensuring proactive maintenance.

The human operator's role is also evident, as decision-making is enhanced through human expertise rather than being fully automated. The factory benefits from predictive maintenance, resource efficiency, and enhanced operational reliability.

A. *IoT Sensing Layer*

The IoT sensing layer is responsible for real-time data collection from the equipment's sensor units. The sensors transmit data to the digital twin using an IoT gateway. The data includes important parameters such as vibrations, temperature, pressure, and operational status.

B. *Digital Twin Layer*

The digital twin receives data continuously from the IoT sensors within the units and machinery. The data received from IoT sensors update the historical data in the storage. The updated data remains a database that can be used for failure prediction purposes. The prediction is an analysis to identify the variation between the historical data and updated data. The digital twin model tests various scenarios with different maintenance approaches using different decision variables before they are implemented in the real system. Implementing the digital twin model improves the model's predictive accuracy and reduces the risk included in maintenance decisions.

C. *Human Interaction Optimization Layer*

Human interaction optimization contributes by integrating real-time user preferences, domain expertise, and adaptive decision-making feedback into the optimization process. By using the enhanced PSO algorithm with human-in-the-loop adaptation, the aim is to reduce cost, increase reliability, and enhance safety.

The human interface actively gathers inputs, including operator adjustments, expert-driven parameter tuning, heuristic insights, and contextual awareness, ensuring the optimization process remains dynamic and responsive to real-world conditions. Unlike traditional autonomous optimization approaches, this framework allows human operators to inject qualitative judgment, adjust constraints, and fine-tune algorithmic parameters in response to environmental changes, operational demands, or unexpected anomalies.

To facilitate seamless human-machine collaboration, the system employs interactive dashboards, real-time monitoring tools, and feedback loops that provide users with actionable insights and performance metrics. These interfaces enable operators to analyze optimization trends, compare different parameter configurations, and introduce modifications that align with specific operational goals such as energy efficiency, resource allocation, or fault tolerance.

Furthermore, integrating AI-driven decision support systems enhances the interaction layer by offering suggestive feedback mechanisms, predictive analytics, and scenario-based recommendations. This ensures that human inputs are reactive and proactive in anticipating challenges, mitigating risks, and optimizing outcomes.

By embedding human expertise within the optimization cycle, the system achieves a hybrid intelligence approach, where algorithmic efficiency is complemented by human intuition, strategic reasoning, and contextual adaptability. This ultimately leads to a more robust, adaptive, and user-centric optimization framework.

IV. METHODOLOGY

The maintenance prediction operation has multiple inputs and a single output. The inputs are considered to be multi-objective functions that produce an efficient system output. The multi-objective functions are represented with different parameters as input to the system. The introduced optimization method fine-tunes the parameter values to yield the most efficient system output. The typical multi-objective parameters are sensor data, historical repair, operational feedback, and asset condition data.

The introduced optimization method uses the best of three different algorithms to produce an accurate solution. The algorithms are known as PSO, RL, and Bayesian optimization algorithms. The PSO optimization can consider multiple input parameters to form a correlation between variables and increase the system's efficiency. The RL optimization uses feedback from the system to update the learning procedure. The updated learning procedure enables accurate decisions to be taken with real data. The system operating under such conditions is classified as a dynamic operation. The Bayesian optimization algorithm can fine-tune the parameters for such an operation.

The combinational use of three methods increases the system's reliability and accuracy. Initially, the PSO considers a large number of solution functions but reduces to the most accurate solution to yield the most accurate output. The RL algorithm continuously monitors the system's behaviour and feeds back to update the historical data. The Bayesian algorithm provides more accurate results for the maintenance prediction operation. The combinational use of three algorithms provides accuracy for maintenance prediction at minimum periods and minimizes the overall cost of the operation.

The enhanced combination of the introduced optimization is described in Algorithm I.

ALGORITHM I. ENHANCED OPTIMIZATION

Parameter Definitions:

- **swarm_size (N)**: Number of particles
- **dimensions (D)**: Size of the problem (number of parameters to be optimized)
- **max_iter**: Maximum number of iterations
- **w**: Inertia weight (coefficient of preservation of the previous speed of the particles)
- **c1**: Cognitive coefficient (coefficient of attraction of a particle to its best solution)
- **c2**: Social coefficient (coefficient of regression to the best solution in the swarm)
- **v_min, v_max**: Speed limits
- **x_min, x_max**: Position limits

<u>Step 1:</u> Initialization Process for the particles

1. For each and individual particle:
   - [x_min, x_max] ⟵ random selection
   - [v_min, v_max] ⟵ random selection
   - Set the best local position of the particle as the starting position.
2. Set the particle's best local fitness value to infinity.
   - Set the best global position in the swarm equal to the position of a random particle.
   - Set the global best fitness value to infinity.

<u>Step 2:</u> Use RL and PSO for maintenance planning

1. Start a loop and process the following

   Adaptively schedule maintenance tasks using the RL model:
   - The RL model determines which maintenance tasks to perform and when based on real-time data from IoT sensors.
   - The model plans maintenance with a dynamic decision process based on safety, cost and failure risks.
2. PSO Main Loop (Iterations): iter = 1 to max_iter:

   For each particle:
   - Calculate the fitness function of the particle.
   - If the current fitness is smaller than the best local fitness of the particle:
     - Update the particle's best local position.
     - Update the particle's best local fitness value.
   - If current fitness is less than the global best overall fitness:
     - Update best global position.
     - Update global fitness best.

   For each particle:
   - Update the particle's speed:

     $$v[i] = w \cdot v[i] + c1 \cdot \mathrm{random}() \cdot (p\_best[i] - x[i]) + c2 \cdot \mathrm{random}() \cdot (g\_best - x[i])$$
   - limit speed

     $$v[i] = max(min(v[i], v\_max), v\_min)$$
   - update the particle's location

     $$x[i] = x[i] + v[i]$$
   - limit position

     $$x[i] = max(min(x[i], x\_\mathrm{max}), x\_min)$$
3. Complete the Iteration

<u>Step 3:</u> Fine-Tuning Model Parameters with Bayesian Optimization

- Optimize model parameters with Bayesian optimization using parameters obtained from PSO:

- Bayesian Optimization improves the accuracy of the predictive maintenance model by fine-tuning model parameters.
- This process is used to improve the performance and accuracy of the model, based on operational data.

- According to the Bayesian model results, the model parameters used in the maintenance process are dynamically updated and optimized.

Step 4: Combining Results with PSO, RL and Bayesian

- At the end of each iteration:
  - PSO updates the position of particles and searches for the best solution.
  - RL model performs adaptive maintenance planning and determines the most appropriate maintenance processes.
  - Bayesian Optimization makes model parameters more precise.
  - As a result, maintenance costs are minimized, and fault prediction accuracy is increased.

End Last Repeat

Step 5: Finalizing the Solution

- The best global position g_best is considered as the optimal solution.
- The best global fitness value fitness_g_best refers to the best fitness result of the solution.
- Optimized parameters as a result of Bayesian Optimization increase the model's prediction accuracy.

Output:

- g_best: Optimal solution (best global position)
- fitness_g_best: Optimal fitness value
- RL Plan: Adaptive maintenance plan determined by RL
- Bayesian Optimized Parameters: Fine-tuned model parameters

V. Simulations and Results

A. Simulation Setup

The details of the equipment used in the simulation are described below.

- Operating System: Windows 11 Pro, 64-bit.
- Processor: Intel Core i9-12900K, 16 cores with a base clock speed of 3.2 GHz and turbo boost up to 5.2 GHz.
- RAM: 64 GB DDR4, operating at 3600 MHz
- Storage: 2 TB NVMe SSD for primary storage and 4 TB SATA SSD for data storage and backup.
- Graphics Processing Unit (GPU): NVIDIA RTX 3080 Ti, 12 GB GDDR6X memory.
- MATLAB Version: MATLAB R2024a with Signal Processing, Communication System, and Neural Network Toolboxes.
- Programming Language: MATLAB with integrated C/C++ MEX files for optimized computational performance.
- Compiler: Microsoft Visual Studio 2022 C++ Compiler (for MEX file compilation).
- Additional Toolboxes: Optimization Toolbox and Statistics and Machine Learning Toolbox for model analysis and verification.
- Parallel Computing Setup: Utilized MATLAB's Parallel Computing Toolbox with up to 12 workers (parallel threads) for simulation acceleration.

The predictive maintenance model in this work is trained and validated using a publicly available Kaggle dataset, which consists of sensor readings and operational data collected from industrial equipment.

The dataset comprises 23,000 samples with multiple sensor readings collected over time, covering different operational states of industrial machines. Each sample represents a time-series instance with various sensor parameters.

The dataset includes multiple sensor modalities, such as temperature, vibration, pressure, rotation speed, and power consumption, allowing for comprehensive failure pattern recognition.

The dataset provides labelled failure instances, distinguishing between normal operation, early warning signs, and critical failures. These labels are essential for supervised learning and model evaluation.

The dataset includes data from various machine types and operating conditions, enabling robust model generalization.

The dataset follows a time-series structure, allowing for trend analysis and early fault detection using sequential modelling techniques.

By leveraging this dataset, the proposed model ensures that the proposed predictive maintenance model is trained on diverse, real-world industrial scenarios, improving its fault detection accuracy and adaptability to varying operational conditions.

The maintenance intervals are realistic to show the true performance of the proposed model. Initially, the proposed algorithm iteratively generated possible solutions for the maintenance schedules using the defined objective functions. The enhanced PSO algorithm helps to escape local minima and improves the quality of the solution. The improved algorithm has introduced its significant values using the methods listed below.

- Adjust Weighting Factors: Modify the outputs more significantly.
- Enhance Local Search: The number of iterations in the local search was increased, and a more sophisticated local search strategy, such as gradient descent, was implemented.

- Dynamic Parameters: Adaptive parameters are adopted in the operation to change the iteration or performance metrics, leading to better solution space exploration.
- Added Constraints: Added constraints guide the search towards feasible results and potentially produce more optimal solutions based on the specific context of the optimization problem.

The algorithm aims to use performance matrices such as maintenance interval, cost, downtime, and reliability score. The performance achievement of the matrices can be described below.

Maintenance Interval (Hours):

The selection of the maintenance interval is a critical performance metric. The purpose of these metrics is to balance system downtime and preventive maintenance. The time taken for a repair may be shorter, but it may increase the maintenance cost. Therefore, the balance between the two parameters must be selected carefully. The other effective point is that longer maintenance periods may increase the failure rates. The optimization algorithm adjusts the interval to minimize unexpected breakdowns and helps to increase the equipment's lifespan.

Cost:

The cost of the operation is a key factor in identifying the financial maintenance strategy. Comparing the unplanned downtime and the optimized preventive maintenance yields the system's efficiency. The resulting output produces a cost-benefit analysis to justify the investment in IoT-based predictive maintenance technologies.

Downtime:

The downtime parameter indicates the efficiency of equipment and machinery. It directly increases productivity efficiency in the case of predictive planning against downtime. In a predictive maintenance algorithm, downtime reduces the time devices remain out of operation.

Reliability:

The reliability factor is directly related to the system's performance over time. It prevents devices from being out of service in critical situations, ensures smooth operation, and prevents unexpected breakdowns. A high-reliability value indicates the system's robustness and ability to promptly meet expected demand.

VI. RESULTS

The proposed algorithm considerably reduces the maintenance intervals for all equipment in operation. The maintenance intervals and scheduling were analyzed to reveal the algorithm's applicability. Results are plotted in Figure IV for visual examination.

Figure IV demonstrates the difference between normal and optimized maintenance intervals. The plots show the reduction of optimized maintenance gain in hours. The data in the simulation improved between 10 to 100 hours of maintenance duration. The overall cost reduces as the maintenance interval reduces. The PSO algorithm sets the maintenance intervals to 150 hours for all equipment indices. This occurs due to the PSO-based approach optimizing maintenance scheduling using real-time equipment data from Kaggle while maintaining a fixed threshold. The proposed method, however, refines the decision criteria, enabling dynamic adjustments to maintenance intervals and resulting in a more flexible and efficient scheduling strategy.

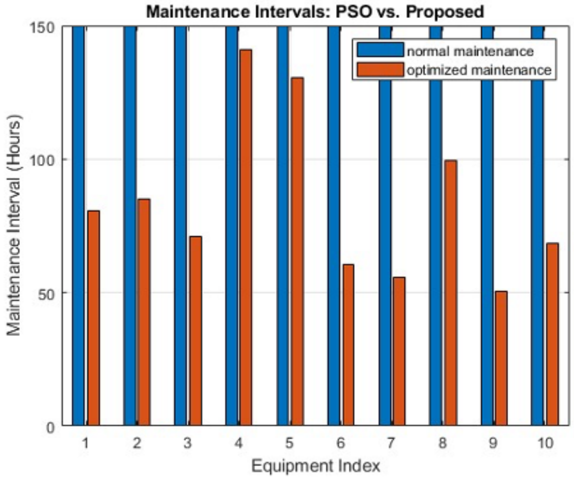

FIGURE IV. COMPARISON OF THE MAINTENANCE INTERVALS

The other parameter to consider is the maintenance cost. Figure V compares and plots the proposed and the most suitable PSO algorithms.

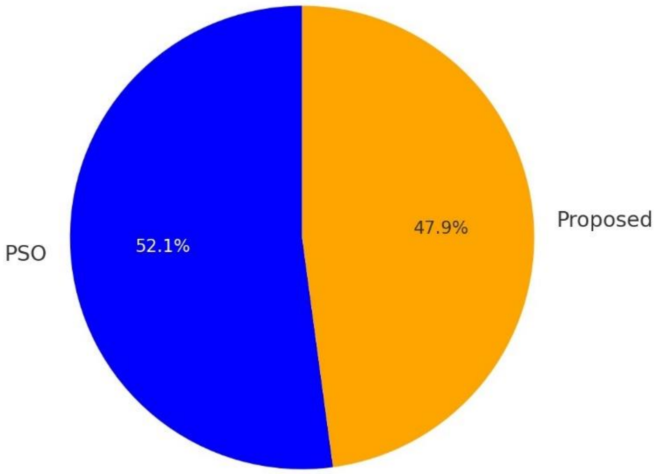

FIGURE V. COST COMPARISON OF THE MAINTENANCE

The cost reduction plots in Figure V. show the efficiency of the proposed method. The results prove that the proper allocation of resources minimizes unnecessary interactions and concentrates on predictive maintenance that avoids costly repairs. The execution of the proposed method yields results as:

Total Cost with Optimized Maintenance Intervals: $44600.00

Cost Reduction: 15.72%

Cost reduction is significant for large manufacturing industries.

The other effective parameter is to analyze the system's total downtime. The downtime analysis is compared with the PSO algorithm, and the results are plotted in Figure VI.

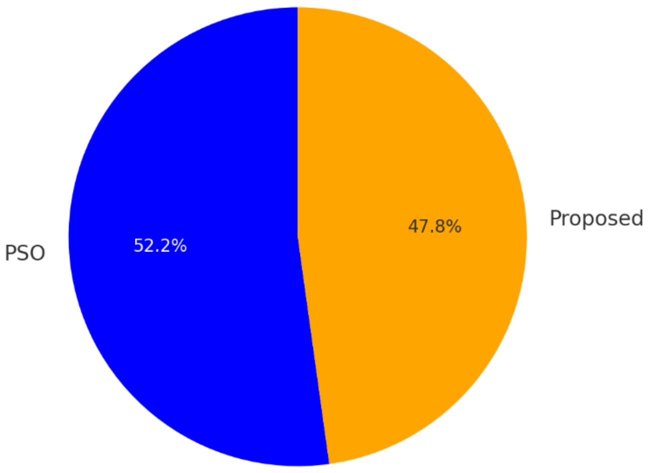

FIGURE VI. COMPARISON OF THE TOTAL DOWNTIME

The total downtime under the proposed method is lower than that of the PSO-based method. The reduction in this dataset is approximately 13 hours, which means the equipment remains operational for longer periods, improving overall system availability and productivity.

The proposed algorithm was further examined using performance metrics such as the reliability score. The results are compared and plotted in Figure VII.

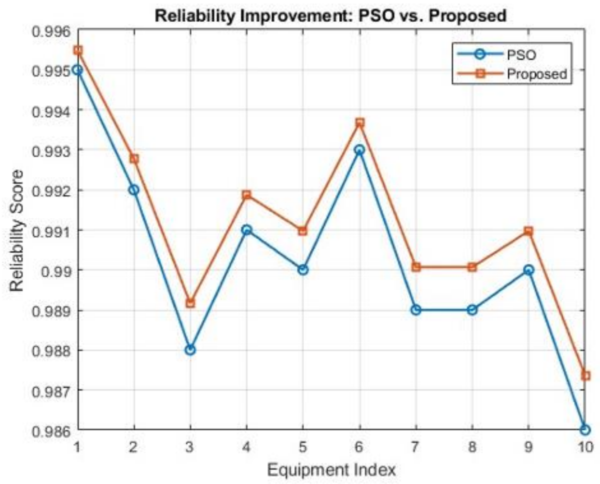

FIGURE VII. RELIABILITY ACHIEVEMENT

The reliability score identifies the success of the system operation. The proposed method scored a higher reliability value for all equipment indices. The higher reliability score is considered a performance measure to suggest that the proposed method is more robust and resilient, especially for critical assets. The resulting reliability score guarantees the equipment to meet the demands, increase the system's robustness, and reduce unexpected failures.

VII. CONCLUSION

The proposed IoT-based predictive maintenance model considered well-known performance measure matrices to evaluate its success. The model uses real data to show its applicability in real-time operations and is compared with a well-known PSO algorithm. The proposed model reduces the maintenance cost by 15.72%. The tested performance metrics such as the maintenance interval, system reliability, and downtime demonstrated high improvements.

The results indicate that the proposed model is superior in terms of offering successful maintenance scheduling, reducing maintenance intervals, and increasing the lifespan of the equipment. The model prevents unexpected failures from occurring that are costly in manufacturing.

The comparison algorithms demonstrate the superiority of the proposed model by minimizing equipment downtime, enhancing operational availability, and increasing productivity. The system's robustness, demonstrated by the reliability score, proves the efficacy of the proposed framework.

The results validate the proposed model to provide a superior solution for predictive maintenance that offers a less costly and better maintenance strategy. The study also reveals another important factor that demonstrates that the proposed model has the potential to be integrated with IoT-based systems for maintenance management in Industry 5.0.

However, several limitations of the proposed method must be considered. One of the primary concerns is the subjectivity and accuracy of human inputs. In industrial settings, the quality of data gathered from human-operated sensors or devices may vary, leading to inconsistencies that can affect the model's predictions. Such inaccuracies could influence the system's overall performance, particularly in environments with more prevalent human error. Future work can address this by improving data collection processes, integrating advanced automation, and using more reliable sensor technologies to reduce human dependency.

Additionally, the proposed model's scalability for large-scale industrial systems remains a challenge. As the system's complexity increases, so does the computational demand, which may affect the model's applicability in larger operations. Exploring ways to optimize computational efficiency, such as through cloud computing or parallel processing, could make the model more feasible for use in larger industrial settings.

For future work, more specific research directions can be pursued. Applying the model across different industrial sectors, such as energy, transportation, or manufacturing, would provide valuable insights into its adaptability and performance in varying contexts. Testing the model with diverse datasets from multiple industries would help identify potential challenges and allow for further system refinement. Additionally, further integration of the model with IoT-based systems, particularly in Industry 5.0, could provide new opportunities for automating maintenance decisions and incorporating advanced machine learning techniques for continuous optimization.

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AUTHORS` CONTRIBUTIONS

All authors have participated in drafting the manuscript. All authors read and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors certify that there is no conflict of interest with any financial organization regarding the material discussed in the manuscript.

DATA AVAILABILITY

The data supporting the findings of this study are available upon request from the authors.

ETHICAL STATEMENT

This article followed the principles of scientific research and publication ethics. This study did not involve human or animal subjects and did not require additional ethics committee approval.

DECLARATION OF AI USAGE

The complete framework architecture was generated using ChatGPT.

REFERENCES

[1] Deepu, T. S., & Ravi, V. (2021). Exploring critical success factors influencing adoption of digital twin and physical internet in electronics industry using the grey-DEMATEL approach. *Digital Business*, *1*(2), 100009. https://doi.org/10.1016/j.digbus.2021.100009

[2] del Campo, G., Saavedra, E., Piovano, L., Luque, F., & Santamaria, A. (2024). Virtual Reality and Internet of Things Based Digital Twin for Smart City Cross-Domain Interoperability. *Applied Sciences*, *14*(7), 2747. https://doi.org/10.3390/app14072747

[3] Bisanti, G. M., Mainetti, L., Montanaro, T., Patrono, L., & Sergi, I. (2023). Digital twins for aircraft maintenance and operation: A systematic literature review and an IoT-enabled modular architecture. *Internet of Things*, 100991. https://doi.org/10.1016/j.iot.2023.100991

[4] Trendowicz, A., Groen, E. C., Henningsen, J., Siebert, J., Bartels, N., Storck, S., & Kuhn, T. (2023). User experience key performance indicators for industrial IoT systems: A multivocal literature review. *Digital Business*, *3*(1), 100057. https://doi.org/10.1016/j.digbus.2023.100057

[5] Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023). Overview of predictive maintenance based on digital twin technology. *Heliyon*, *9*(4). https://doi.org/10.1016/j.heliyon.2023.e14534

[6] Yao, J. F., Yang, Y., Wang, X. C., & Zhang, X. P. (2023). Systematic review of digital twin technology and applications. *Visual Computing for Industry, Biomedicine, And Art*, *6*(1), 10. https://doi.org/10.1186/s42492-023-00137-4

[7] Moshood, T. D., Rotimi, J. O., Shahzad, W., & Bamgbade, J. A. (2024). Infrastructure digital twin technology: A new paradigm for future construction industry. *Technology in Society*, *77*, 102519. https://doi.org/10.1016/j.techsoc.2024.102519

[8] Arowoiya, V. A., Moehler, R. C., & Fang, Y. (2024). Digital twin technology for thermal comfort and energy efficiency in buildings: A state-of-the-art and future directions. *Energy and Built Environment*, *5*(5), 641-656. https://doi.org/10.1016/j.enbenv.2023.05.004

[9] Van Oudenhoven, B., Van de Calseyde, P., Basten, R., & Demerouti, E. (2023). Predictive maintenance for industry 5.0: Behavioural inquiries from a work system perspective. *International Journal of Production Research*, *61*(22), 7846-7865. https://doi.org/10.1080/00207543.2022.2154403

[10] Murtaza, A. A., Saher, A., Zafar, M. H., Moosavi, S. K. R., Aftab, M. F., & Sanfilippo, F. (2024). Paradigm Shift for Predictive Maintenance and Condition Monitoring from Industry 4.0 to Industry 5.0: A Systematic Review, Challenges and Case Study. *Results in Engineering*, 102935. https://doi.org/10.1016/j.rineng.2024.102935

[11] Ejjami, R., & Boussalham, K. (2024). Resilient Supply Chains in Industry 5.0: Leveraging AI for Predictive Maintenance and Risk Mitigation. *International Journal for Multidisciplinary Research*, *6*(4), 1-32. https://doi.org/10.36948/ijfmr.2024.v06i04.25116

[12] Frick, J. (2023). Future of industrial asset management: A synergy of digitalization, digital twins, maintenance 5.0/quality 5.0, industry 5.0 and iso55000. *International Journal of Business Marketing and Management*, *8*(4), 93-99.

[13] Adel, A. (2023). Unlocking the future: fostering human–machine collaboration and driving intelligent automation through industry 5.0 in smart cities. *Smart Cities*, *6*(5), 2742-2782. https://doi.org/10.3390/smartcities6050124

[14] Pizoń, J., & Gola, A. (2023). Human–machine relationship—perspective and future roadmap for industry 5.0 solutions. *Machines*, *11*(2), 203; 1-22. https://doi.org/10.3390/machines11020203

[15] Alves, J., Lima, T. M., & Gaspar, P. D. (2023). Is industry 5.0 a human-centred approach? a systematic review. *Processes*, *11*(1), 193;1-15. https://doi.org/10.3390/pr11010193

[16] Marinelli, M. (2023). From Industry 4.0 to Construction 5.0: Exploring the Path towards Human–Robot Collaboration in Construction. *Systems*, *11*(3), 152; 1-23. https://doi.org/10.3390/systems11030152

[17] Peruzzini, M., Prati, E., & Pellicciari, M. (2024). A framework to design smart manufacturing systems for Industry 5.0 based on the human-automation symbiosis. *International journal of computer integrated manufacturing*, *37*(10-11), 1426-1443. https://doi.org/10.1080/0951192X.2023.2257634

[18] Zafar, M. H., Langås, E. F., & Sanfilippo, F. (2024). Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review. *Robotics and Computer-Integrated Manufacturing*, *89*, 102769. https://doi.org/10.1016/j.rcim.2024.102769

[19] Zhang, C., Wang, Z., Zhou, G., Chang, F., Ma, D., Jing, Y., ... & Zhao, D. (2023). Towards new-generation human-centric smart manufacturing in Industry 5.0: A systematic review. *Advanced Engineering Informatics*, *57*, 102121. https://doi.org/10.1016/j.aei.2023.102121

[20] Calzavara, M., Faccio, M., & Granata, I. (2023). Multi-objective task allocation for collaborative robot systems with an Industry 5.0 human-centered perspective. *The International Journal of Advanced Manufacturing Technology*, *128*(1-2), 297-314. https://doi.org/10.1007/s00170-023-11673-x

[21] Huang, W., Liu, Y., & Zhang, X. (2023). Hybrid particle swarm optimization algorithm based on the theory of reinforcement learning in psychology. *Systems*, *11*(2), 83. https://doi.org/10.3390/systems11020083

[22] Hu, S., & Li, K. (2023). Bayesian network demand-forecasting model based on modified particle swarm optimization. *Applied Sciences*, *13*(18), 10088. https://doi.org/10.3390/app131810088

[23] Abdul Karim, S. A., & Tamin, O. (2024). Intelligent System Modeling in Industrial 4.0. In *Intelligent Systems Modeling and Simulation III: Artificial Intelligent, Machine Learning, Intelligent Functions and Cyber Security* (pp. 1-13). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-67317-7_1

[24] Soesanto, J. (2024). *Digital Twin and Smart Automation for Bitumen Extraction Process*. [Master thesis, University of Alberta]. University of Alberta Education and Research Archive. https://doi.org/10.7939/r3-wgex-2h6

[25] Marugán, A. P. (2023). Applications of Reinforcement Learning for maintenance of engineering systems: A review. *Advances in*

Engineering Software, *183*, 103487. https://doi.org/10.1016/j.advengsoft.2023.103487

[26] Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., & Mrozek, D. (2023). From corrective to predictive maintenance—A review of maintenance approaches for the power industry. *Sensors*, *23*(13), 5970. https://doi.org/10.3390/s23135970

[27] Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023). Overview of predictive maintenance based on digital twin technology. *Heliyon*, *9*(4). https://doi.org/10.1016/j.heliyon.2023.e14534

[28] Abouelyazid, M. (2023). Advanced Artificial Intelligence Techniques for Real-Time Predictive Maintenance in Industrial IoT Systems: A Comprehensive Analysis and Framework. *Journal of AI-Assisted Scientific Discovery*, *3*(1), 271-313.

[29] Qiu, S., Cui, X., Ping, Z., Shan, N., Li, Z., Bao, X., & Xu, X. (2023). Deep learning techniques in intelligent fault diagnosis and prognosis for industrial systems: a review. *Sensors*, *23*(3), 1305. https://doi.org/10.3390/s23031305

[30] Meriem, H., Nora, H., & Samir, O. (2023). Predictive maintenance for smart industrial systems: a roadmap. *Procedia Computer Science*, *220*, 645-650. https://doi.org/10.1016/j.procs.2023.03.082

[31] Rahman, M. S., Ghosh, T., Aurna, N. F., Kaiser, M. S., Anannya, M., & Hosen, A. S. (2023). Machine learning and internet of things in industry 4.0: A review. *Measurement: Sensors*, *28*, 100822. https://doi.org/10.1016/j.measen.2023.100822

[32] van Dinter, R., Tekinerdogan, B., & Catal, C. (2023). Reference architecture for digital twin-based predictive maintenance systems. *Computers & Industrial Engineering*, *177*, 109099. https://doi.org/10.1016/j.cie.2023.109099

[33] Weerapura, V., Sugathadasa, R., De Silva, M. M., Nielsen, I., & Thibbotuwawa, A. (2023). Feasibility of digital twins to manage the operational risks in the production of a ready-mix concrete plant. *Buildings*, *13*(2), 447. https://doi.org/10.3390/buildings13020447

[34] Boumallessa, Z., Chouikhi, H., Elleuch, M., & Bentaher, H. (2023). Modeling and optimizing the maintenance schedule using dynamic quality and machine condition monitors in an unreliable single production system. *Reliability Engineering & System Safety*, *235*, 109216. https://doi.org/10.1016/j.ress.2023.109216

[35] Khan, M. F. I., & Masum, A. K. M. (2024). Predictive Analytics And Machine Learning For Real-Time Detection Of Software Defects And Agile Test Management. *Educational Administration: Theory and Practice*, *30*(4), 1051-1057.