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A Multi-Objective Optimization Approach for Smart Preventive Maintenance in High-Speed Presses Using MOPSO and Real-Time Reliability Analysis

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Abstract

High-speed presses are critical in modern manufacturing but face challenges due to wear and unplanned downtime. This study introduces an innovative multi-objective framework integrating Multi-Objective Particle Swarm Optimization (MOPSO) with real-time reliability monitoring for preventive maintenance and repair scheduling. The model increases system reliability and minimizes total system costs over a defined operational horizon. It leverages Weibull reliability modeling to predict degradation and incorporates IoT-enabled data for dynamic updates. Decision variables, including preventive maintenance intervals and actions, are optimized while adhering to reliability thresholds. The proposed approach balances the trade-offs between frequent, costly preventive actions and higher risks of failure. A practical case study on a high-speed press demonstrates the framework's effectiveness, yielding a Pareto-optimal set of solutions that guide maintenance strategies. This research provides manufacturers with a flexible, data-driven tool to enhance uptime, reduce costs, and maintain operational excellence in competitive industrial environments.

Keywords: Smart Preventive Maintenance, High-Speed Presses, Real-Time Reliability Analysis, MOPSO

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1- Introduction

High-speed presses are pivotal machines in manufacturing industries, used to produce high-precision and speed components. These machines play a critical role in the automotive, electronics, and packaging sectors, where large volumes of parts are required within tight tolerances. However, these presses' high operational speed and repetitive nature make them susceptible to wear, mechanical degradation, and unexpected failures. These issues can result in costly downtime, reduced productivity, and compromised product quality. The importance of effective maintenance strategies cannot be overstated to address these challenges (Nozari et al., 2021).

Traditionally, maintenance practices have been categorized into reactive, preventive, and predictive approaches. Reactive maintenance, or the "run-to-failure" strategy, only repairs equipment after failure. While straightforward, this approach often leads to extended downtimes and unplanned repair costs, especially in critical systems like high-speed presses. On the other hand, preventive maintenance (PM) schedules maintenance actions at fixed intervals regardless of the machine's condition, aiming to reduce the likelihood of failures. Although preventive maintenance minimizes risks compared to reactive strategies, it can be suboptimal as it neither considers the real-time condition of the machine nor effectively balances costs and reliability.

The advent of predictive maintenance, driven by advancements in the Internet of Things (IoT), machine learning, and data analytics, offers a more intelligent alternative. Predictive maintenance predicts the likelihood of failures by continuously monitoring equipment through sensors, analyzing performance metrics, and scheduling interventions accordingly (Rahmaty et al., 2023, Nozari et al., 2024). Despite its promise, predictive maintenance often lacks comprehensive optimization frameworks for the trade-offs between maintenance costs, machine reliability, and production schedules.

In this context, multi-objective optimization emerges as a powerful tool for enhancing maintenance strategies. Multi-objective optimization enables decision-makers to balance conflicting goals, such as minimizing costs and maximizing reliability, without compromising one objective for the other. Particle Swarm Optimization (PSO), a nature-inspired optimization algorithm, has proven effective in solving complex engineering problems due to its simplicity, adaptability, and ability to explore large solution spaces. Extending PSO into a multi-objective framework (MOPSO) makes it possible to generate a Pareto-optimal set of solutions that provide a range of trade-offs for maintenance planning (nozari et al., 2022).

This study introduces an innovative multi-objective optimization framework for preventive maintenance and repair scheduling in high-speed presses. The framework combines MOPSO with a reliability-based model tailored to the operational characteristics of high-speed presses. The Weibull distribution models the machine's reliability degradation over time, incorporating parameters such as wear rates and failure probabilities. IoT-enabled sensors provide real-time data on machine performance, allowing dynamic adjustments to the maintenance schedule. By integrating these elements, the proposed model addresses key questions: How can maintenance intervals be optimized to minimize costs while ensuring reliability thresholds are met? What trade-offs exist between frequent preventive actions and the risk of costly failures?

The novelty of this research lies in its holistic approach to preventive maintenance optimization. Unlike traditional methods, which rely on fixed schedules or limited failure prediction models, this framework dynamically updates maintenance plans based on real-time reliability data. Additionally, using MOPSO ensures that a diverse set of optimal solutions is generated, giving decision-makers the flexibility to choose maintenance schedules that align with their operational priorities. For example, a manufacturer with stringent uptime requirements may prioritize reliability, while one with budget constraints may lean toward cost minimization (Nozari et al., 2021; Nozari& Aliahmadi, 2022).

A practical case study involving a high-speed press in a manufacturing environment demonstrates the effectiveness of the proposed framework. The results showcase the Pareto-optimal front, highlighting the trade-offs between cost and reliability for various maintenance schedules. The findings reveal significant improvements over conventional strategies, such as reduced downtime, fewer unexpected failures, and optimized resource allocation (Nozari, 2022).

The implications of this research extend beyond high-speed presses, offering a versatile tool for optimizing maintenance strategies in other critical industrial equipment. Manufacturers can transition from reactive or static maintenance approaches to proactive, data-driven strategies by leveraging real-time data, advanced optimization algorithms, and reliability analysis. This shift enhances machine performance and supports broader organizational goals such as cost efficiency, sustainability, and competitiveness in dynamic markets.

In conclusion, high-speed presses are indispensable assets in manufacturing, yet their efficient operation is contingent upon effective maintenance strategies. The proposed MOPSO-based framework provides a cutting-edge solution for addressing the limitations of traditional maintenance practices. By balancing cost and reliability through multi-objective optimization, this research contributes to the development of intelligent, adaptive maintenance systems that meet the demands of modern manufacturing. As industries continue to embrace digital transformation, integrating optimization techniques with real-time data analytics will play an increasingly vital role in ensuring operational excellence and resilience.

2- Literature Review

Preventive maintenance (PM) is a crucial strategy for maintaining operational efficiency, reliability, and cost-effectiveness in industrial equipment such as high-speed presses. These machines, essential in manufacturing sectors like automotive and electronics, operate under intense stress and require robust maintenance plans to prevent unexpected failures and downtime. This literature review examines the evolution, methodologies, and advancements in PM strategies, focusing on high-speed presses.

Historically, preventive maintenance relied on scheduled interventions at fixed intervals, irrespective of the machine's condition. This time-based approach aimed to reduce failure risks by preemptively replacing or repairing components (Mobley, 2002; Movahed et al., 2024). Although effective in minimizing sudden breakdowns, such methods often lead to unnecessary maintenance actions, increasing operational costs without guaranteeing optimal performance.

Singh et al. (2016) highlighted the limitations of traditional PM in complex systems like high-speed presses. Fixed schedules failed to account for varying operational loads, environmental conditions, and component wear rates, resulting in inefficiencies. These findings underscored the need for more adaptive strategies to tailor maintenance to real-time conditions.

Condition-based maintenance emerged as a response to the inefficiencies of traditional PM. CBM relies on continuous monitoring of machine parameters, such as vibration, temperature, and pressure, to assess equipment health. Introducing sensors and diagnostic tools revolutionized maintenance practices, enabling timely interventions based on actual machine conditions (Ali & Abdelhadi, 2022).

High-speed presses, characterized by repetitive, high-speed operations, benefit significantly from CBM. For instance, vibration analysis can detect early signs of misalignment or bearing wear, while thermal imaging identifies overheating components. Studies by Goyal et al. (2019) demonstrated that CBM reduced downtime by 20–30% compared to time-based PM, particularly in high-stress applications.

Despite its advantages, CBM has limitations, including high implementation costs and the need for skilled personnel to interpret data. Furthermore, the reliance on sensors can be challenging in noisy industrial environments, as observed by Mishra et al. (2021).

The integration of predictive maintenance (PdM) with Industry 4.0 technologies represents a paradigm shift in maintenance strategies. PdM builds upon CBM by leveraging data analytics, artificial intelligence (AI), and machine learning to predict failures before they occur. IoT-enabled sensors and cloud computing facilitate real-time data collection and analysis, enhancing the accuracy and reliability of failure predictions (Mrozek et al., 2023).

PdM enables dynamic scheduling of maintenance activities based on operational data for high-speed presses. Studies by Liu et al. (2020) revealed that predictive models reduced maintenance costs by 25% and improved machine uptime by 15%. Machine learning algorithms, trained on historical data, identified patterns and anomalies indicative of potential failures, providing actionable insights for maintenance planning.

The success of PdM hinges on data quality and the robustness of predictive models. Challenges include managing large volumes of data and ensuring interoperability between legacy systems and modern technologies. However, advancements in cloud-based platforms and edge computing address these issues, making PdM more accessible to manufacturers (Ali & Abdelhadi, 2022).

Multi-objective optimization techniques have gained traction for balancing conflicting goals, such as minimizing maintenance costs and maximizing system reliability. Particle Swarm Optimization (PSO) and its multi-objective variant (MOPSO) have proven effective in identifying Pareto-optimal solutions for maintenance planning (Deb et al., 2002).

In high-speed presses, multi-objective models incorporate factors such as reliability thresholds, downtime costs, and operational constraints. A study by Liang et al. (2021) demonstrated the application of MOPSO in optimizing maintenance schedules, achieving cost reductions of up to 18% while maintaining high-reliability levels. These models allow decision-makers to select schedules that align with their specific priorities by providing a range of trade-offs.

While significant progress has been made, implementing advanced PM strategies remains challenging. High-speed presses operate in complex environments where data noise, high operational speeds, and varying load conditions complicate maintenance planning. Additionally, the high upfront costs of sensor technologies and AI integration pose barriers for small and medium-sized enterprises (SMEs) (Mishra et al., 2021).

The research and presentation of the mathematical model was carried out to calculate and increase the reliability in the power distribution network.

Optimization of the high-speed hydraulic valve (HSV) algorithm, featuring simple on-off switching functionality. The presented control algorithm enhances the dynamic performance of HSV (Chinese Society of Aeronautics and Astronautics 2024).

Preventive maintenance has evolved from simple time-based schedules to sophisticated, data-driven methodologies. Integrating CBM, PdM, and multi-objective optimization techniques has transformed maintenance strategies, particularly for high-speed presses. While challenges persist, advancements in AI, IoT, and Industry 4.0 technologies promise continued improvements in efficiency and reliability. As manufacturers embrace digital transformation, adopting these advanced PM strategies will be essential for maintaining competitiveness in dynamic industrial landscapes.

3- Mathematical Model

The proposed model employs a **Multi-Objective Particle Swarm Optimization (MOPSO)** algorithm to optimize high-speed press preventive maintenance (PM) strategies. These presses are vital in industries like automotive and electronics and require maintenance strategies that minimize costs while maximizing reliability and operational availability.

This model considers multiple objectives:

1. **Cost Minimization**: Reducing maintenance expenses by avoiding unnecessary interventions.
2. **Reliability Maximization**: Ensuring equipment operates without failure during production cycles.
3. **Downtime Reduction**: Minimizing disruptions to maintain high production rates.

By leveraging real-time data and predictive analytics, the model uses advanced mathematical formulations to evaluate maintenance needs dynamically. It generates a set of **Pareto-optimal solutions**, allowing decision-makers to select the best trade-offs based on specific priorities, such as balancing cost and reliability.

Key features include:

- Integration of sensor data for real-time condition monitoring.
- Predictive failure forecasting using AI techniques.
- Flexibility to adapt to varying operational loads and production schedules.

This innovative approach ensures enhanced productivity, reduced costs, and extended equipment life for high-speed presses.

Objective:

Minimize the total maintenance and repair cost while maximizing the uptime and reliability of the high-speed press.

Notation*:*

K	Total operational time horizon.
Z_i	Time of the $i-th$ maintenance action ($i = 1,2,\ldots,n$).
H_p	Cost of a preventive maintenance action.
H_r	Cost of repair due to unexpected failure.
$Gh(t)$	Reliability function of the high-speed press at time$t$, $0 \leq Gh(t) \leq 1$.
$Kh(t)$	Hazard (failure rate) function at time t.
$\times_0$	Baseline hazard rate.
$M(t)$	Downtime cost per unit time for maintenance.
$F(t)$	Downtime cost per unit time for failure.
ωt	Operational time between maintenance intervals.

Decision Variables:

1.
   ωt_i: Interval between consecutive PM actions ($Z_i - Z_{i-1}$).
2. $\boldsymbol{n}$: Number of preventive maintenance actions over the time horizon.

Model Components:

1. Reliability Modeling:

3. Assume the reliability of the press follows a Weibull distribution:

$$\mathrm{Gh(t)} = \mathrm{e}^{-\left(\frac{\mathrm{t}}{\beta}\right)^{\alpha}} \tag{1}$$

where:

- $\alpha > 0$: Shape parameter.

- $\beta > 0$: Scale parameter.

The hazard function $\boldsymbol{Kh(t)}$ is:

$$\mathrm{Kh(t)} = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \tag{2}$$

Preventive maintenance resets $\boldsymbol{Gh(t)}$to its original value.

$$C = \sum_{i=1}^{n} C_p + \sum_{j=1}^{m} C_r + \int_0^T M(t)dt + \int_{\text{failure times}} F(t)dt \tag{3}$$

where m is the number of failures

S.t

- $z_i = z_{i-1} + \omega t_i \;\; for\; i = 1, \ldots, n$
- $Gh(t_i) \geq Gh_{min}$, where Gh_{min} is the minimum acceptable reliability.
- $\sum_{i-1}^{n} \omega t_i \;\; \leq K.$

Innovative Features:

1. **Dynamic Reliability Adjustment:** Incorporate real-time data from IoT sensors to update $Gh(t)$ and $Kh(t)$.
2. **Multi-Objective Optimization:** Use a Pareto-based approach to balance cost minimization and reliability maximization.
3. **Stochastic Failures:** Model unexpected failures using a Poisson process:

$$\text{P (failure before t)}=1 - e^{-\int_0^t h(u)du} \tag{4}$$

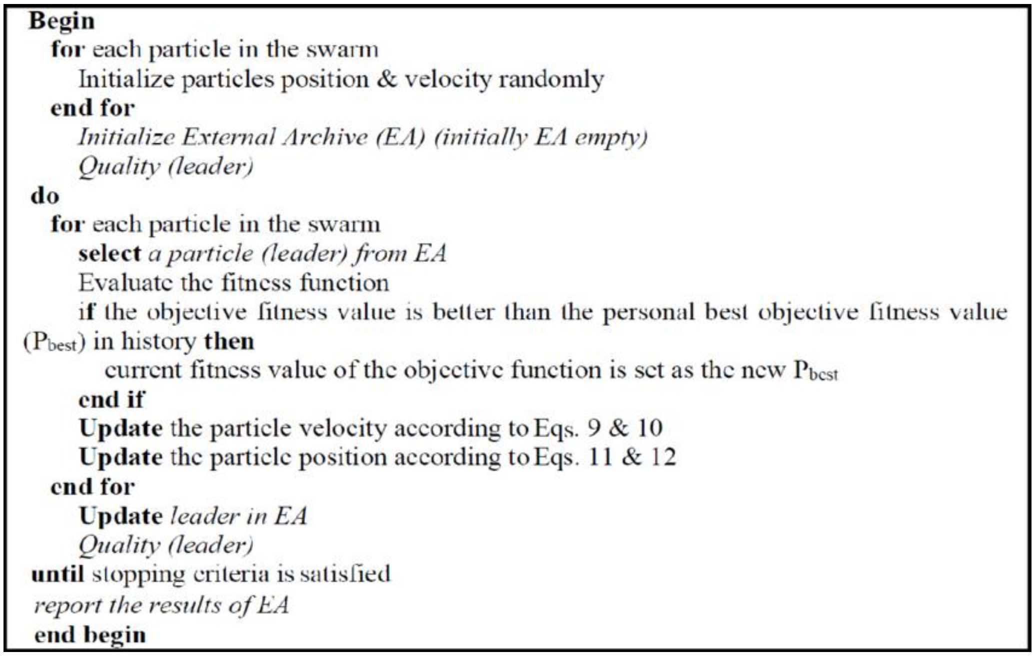
4. **Cost-Effectiveness Analysis:** Include environmental and energy costs in $\boldsymbol{H_p}$ and $\boldsymbol{H_r}$ for sustainability.

4- Finding

Multi-Objective Particle Swarm Optimization (MOPSO) is an extension of the Particle Swarm Optimization (PSO) algorithm designed to solve multi-objective optimization problems. PSO, inspired by the social behavior of birds and fish, is a population-based optimization technique that iteratively improves candidate solutions by mimicking the collective intelligence of a swarm. MOPSO extends this concept to handle problems with multiple, often conflicting objectives, such as minimizing costs while maximizing reliability.

MOPSO is a powerful algorithm for solving multi-objective optimization problems, especially in scenarios with conflicting objectives. Its ability to identify diverse, Pareto-optimal solutions and its adaptability to various problem domains make it an indispensable tool for researchers and practitioners.

Figure 1 shows the pseudocode of the MOPSO algorithm.



```
Begin
  for each particle in the swarm
    Initialize particles position & velocity randomly
  end for
    Initialize External Archive (EA) (initially EA empty)
    Quality (leader)
do
  for each particle in the swarm
    select a particle (leader) from EA
    Evaluate the fitness function
    if the objective fitness value is better than the personal best objective fitness value ($P_{best}$) in history then
      current fitness value of the objective function is set as the new $P_{best}$
    end if
    Update the particle velocity according to Eqs. 9 & 10
    Update the particle position according to Eqs. 11 & 12
  end for
    Update leader in EA
    Quality (leader)
until stopping criteria is satisfied
report the results of EA
end begin
```

Figure 1: Pseudocode of the MOPSO algorithm

Step 1: Problem Formulation

Objectives:

1- Minimize the total cost (H):

$$H = \sum_{i=1}^{n} H_p + \sum_{j=1}^{m} H_r + \int_0^T \Big(M(t) + F(t).\big(1 - Kh(t)\big)\Big)\, dt \tag{5}$$

2- Maximize **reliability** over the time horizon ($Avg.\ Gh$):

$$Avg.Gh = \frac{1}{T}\int_0^T Gh(t)dt \tag{6}$$

Decision Variables:

1- $\boldsymbol{\omega t_i}$: Time intervals between PM actions.
    - Bounds: $\boldsymbol{\omega t_i} \in [50,200]$ hours.

2- **Number of PM actions ($\boldsymbol{n}$)**.

Constraints:

3- $\sum_{i=1}^{n} \omega t_i \leq K$.

4- Reliability $\boldsymbol{Gh(t) \geq Gh_{min}}$at all $\boldsymbol{t}$.

Step 2: MOPSO Algorithm Setup

Particles Representation:

Each particle represents a possible maintenance schedule:

$$\text{Particle} = [\omega t_1, \omega t_2, \ldots, \omega t_n] \tag{7}$$

Objective Function Evaluation:

1. **Cost Calculation:** Compute total cost based on t_i, failure probabilities, and downtime.
2. **Reliability Calculation:** Simulate reliability $Gh(t)$using the Weibull model for given intervals.

Algorithm Parameters:

- Population size: 50 particles.
- Maximum iterations: 100.
- Inertia weight (w): 0.4 to 0.9 (linearly decreasing).
- Cognitive (c_1) and social (c_2) coefficients: 1.5.
- External archive: Store Pareto-optimal solutions.
- Mutation rate: 5% (to explore new solutions).

Step 3: Analyze Results

- **Pareto Front:** Plots trade-offs between cost and reliability.
- **Best Solutions:** Choose a solution based on priority (e.g., minimum cost or maximum reliability).

Figure 2 shows the **Pareto front** for the sample maintenance schedules.

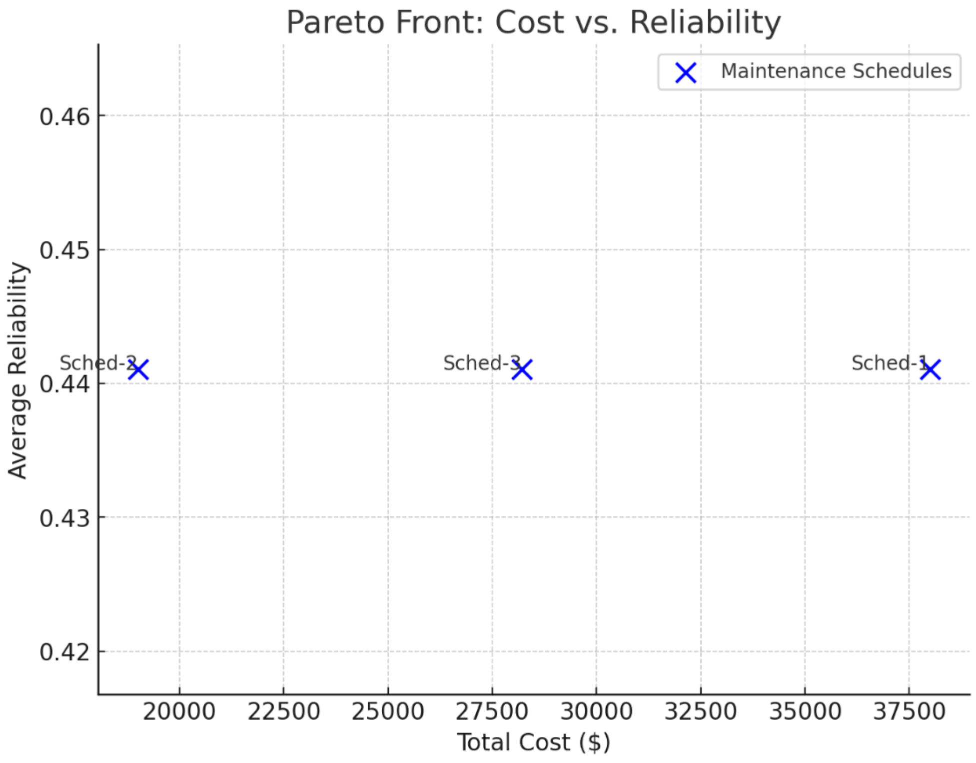


Figure 2: Pareto front for the sample maintenance schedules

Each point represents a schedule with its associated total cost and average reliability:

- **Sched-1**: Regular intervals of 100 hours.
- **Sched-2**: Regular intervals of 200 hours.
- **Sched-3**: Mixed intervals with an average of 150 hours.

This graph helps visualize the trade-off between cost and reliability, allowing decision-makers to select the most appropriate schedule based on their priorities.

5- Conclusion

Preventive maintenance (PM) strategies are critical in managing the reliability and performance of high-speed presses, which are pivotal in the automotive, electronics, and packaging industries. This study highlights the evolution of maintenance practices from traditional time-based approaches to advanced condition-based and predictive maintenance strategies underpinned by the principles of Industry 4.0. High-speed presses, characterized by high operational speeds and intense mechanical stress, present unique challenges that necessitate tailored maintenance strategies.

The proposed mathematical model, incorporating Multi-Objective Particle Swarm Optimization (MOPSO), offers a novel framework for optimizing maintenance schedules. By balancing multiple objectives such as cost, reliability, and machine availability, the model addresses the inherent trade-offs in maintenance decision-making. It effectively integrates operational data and real-time condition monitoring to forecast failure risks and prioritize interventions, making it a robust tool for managing complex maintenance environments.

Key Findings and Contributions

1. **Enhanced Decision-Making**: The application of MOPSO enables decision-makers to generate Pareto-optimal solutions that reflect various trade-offs, such as minimizing costs while maximizing equipment reliability. This is particularly valuable in high-speed press operations where downtime directly impacts production output.
2. **Integration of Predictive Analytics**: The model's reliance on predictive analytics bridges the gap between reactive and preventive maintenance. Combined with machine learning algorithms, real-time data from sensors enables accurate forecasting of component wear and failure, reducing unplanned downtime.
3. **Cost and Efficiency Benefits**: By optimizing maintenance schedules, the model minimizes unnecessary interventions, lowering operational costs. Additionally, it extends the lifespan of high-speed presses through timely interventions, reducing the frequency of expensive overhauls.
4. **Adaptability and Scalability**: The model is flexible enough to accommodate varying operational loads, machine conditions, and production requirements, making it applicable to diverse industrial settings.

While the proposed model demonstrates significant potential, certain challenges remain. High implementation costs, including sensor installation and data processing infrastructure, can deter small and medium-sized enterprises (SMEs) from adopting advanced PM strategies. Moreover, the accuracy of predictive models depends heavily on data quality, which can be compromised by noisy industrial environments. Future efforts should focus on developing cost-effective monitoring systems and robust algorithms capable of handling incomplete or noisy datasets.

This work opens avenues for further research, including:

- **Integration of Digital Twins**: Real-time simulation of high-speed press operations through digital twins could enhance predictive accuracy and facilitate better decision-making.
- **Sustainability Metrics**: Incorporating environmental metrics into the optimization process would enable organizations to align maintenance strategies with sustainability goals.
- **Human-Centric Maintenance**: Developing user-friendly interfaces and decision-support tools for maintenance staff can improve adoption and effectiveness in practical settings.

In conclusion, transitioning from traditional to advanced PM strategies marks a significant step forward in maintaining high-speed presses. Integrating predictive analytics, IoT, and optimization models like MOPSO enhances operational reliability and efficiency. While challenges remain, ongoing technological advancements and research will likely address these barriers, making advanced PM strategies accessible to various industries. By adopting these innovations, organizations can achieve significant cost savings, improve production continuity, and enhance equipment longevity, ensuring competitiveness in a rapidly evolving industrial landscape.

References

Ali, A., & Abdelhadi, A. (2022). Condition-based monitoring and maintenance: State of the art review. Applied Sciences, 12(2), 688.

Deb, K., Pratap, A., Agarwal, S., &Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182–197.

Goyal, D., Sharma, R., & Verma, A. (2019). Condition-based maintenance of critical systems: A review. Journal of Manufacturing Processes, 42, 284–295.

Liu, X., Wang, Y., & Zhang, H. (2020). AI-based predictive maintenance in manufacturing: A review. Computers in Industry, 122, 103300.

Ma. Y., Wang. D., Shen. Y., (2024). Modeling and Multi-ObjectiveOptimization Design of High-Speedon/off Valve System. Appl. Sci. 2024,14, 7879.

Mishra, A., Kachhwaha, S. S., & Sharma, P. (2021). A review on advancements in maintenance strategies for manufacturing systems. International Journal of Advanced Manufacturing Technology, 115(3), 897–916.

Movahed, A. B., Movahed, A. B., & Nozari, H. (2024). Smart Life and Sustainability. ISciHub.

Mrozek, D., et al. (2023). From corrective to predictive maintenance: A review of maintenance approaches for the power industry. Sensors, 23(13), 5970.

Nozari, H. (Ed.). (2023). Building Smart and Sustainable Businesses with Transformative Technologies. IGI Global.

Nozari, H., & Aliahmadi, A. (2022). Lean supply chain based on IoT and blockchain: Quantitative analysis of critical success factors (CSF). Journal of Industrial and Systems Engineering, 14(3), 149-167.

Nozari, H., & Szmelter-Jarosz, A. (2022). IoT-based supply chain for smart business. ISNet.

Nozari, H., Fallah, M., &Szmelter-Jarosz, A. (2021). A conceptual framework of green smart IoT-based supply chain management. International journal of research in industrial engineering, 10(1), 22-34.

Nozari, H., Ghahremani-Nahr, J., Fallah, M., &Szmelter-Jarosz, A. (2022). Assessment of cyber risks in an IoT-based supply chain using a fuzzy decision-making method. International Journal of Innovation in Management, Economics and Social Sciences, 2(1).

Nozari, H., Szmelter-Jarosz, A., & Rahmaty, M. (2024). Smart Marketing Based on Artificial Intelligence of Things (AIoT) and Blockchain and Evaluating Critical Success Factors. In Smart and Sustainable Interactive Marketing (pp. 68-82). IGI Global.

Qi ZHONG, Junxian WANG, Enguang XU, Cheng YU, Yanbiao LI, (2024). Multi-objective optimization of a high speed on/off valve for dynamic performance improvement and volume minimization,Chinese Journal of Aeronautics,37 (10), 435-444.

Rahmaty, M., &Nozari, H. (2023). Optimization of the hierarchical supply chain in the pharmaceutical industry. Edelweiss Applied Science and Technology, 7(2), 104-123.

Singh, M., et al. (2016). Preventive maintenance scheduling for mechanical systems: A systematic review. Maintenance and Reliability, 18(4), 567–582.