Data-Driven Optimization of Cylinder Block Accessibility in Cast Iron Plants Using Machine Learning

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Abstract

Cylinder blocks are critical components in cast iron manufacturing plants, and their availability directly impacts production efficiency. Traditional approaches to maintenance and availability analysis often rely on manual records and heuristic decision-making, which can be inefficient and error-prone. This study leverages machine learning to analyze historical maintenance data, identify patterns, and optimize the availability of cylinder blocks through predictive maintenance strategies.

Keywords: Cylinder Block Availability, Cast Iron Manufacturing, Machine Learning, Predictive Maintenance, Failure Rate Analysis, Repair Rate Optimization, System Reliability, Maintenance Scheduling, Industrial Process Optimization

1. Introduction:

Cylinder blocks are fundamental components used extensively in cast iron manufacturing plants, serving as the core structure within engines and machinery. Their structural integrity and operational availability are vital for maintaining smooth production processes and achieving high efficiency in manufacturing operations. Any unplanned downtime or failure in the cylinder blocks can lead to significant delays, increased costs, and loss of productivity, thereby affecting the overall competitiveness and profitability of the plant. Traditionally, maintenance and availability management in cast iron manufacturing have relied heavily on manual record-keeping and expert judgment. Maintenance personnel track equipment failures, repairs, and downtime through logs and reports, which are then analyzed using heuristic or rule-based methods to schedule inspections and repairs. While these approaches have served the industry for decades, they often suffer from limitations such as human error, inconsistent data quality, and delayed decision-making. Moreover, heuristic methods may not fully capture the complex, nonlinear relationships between various factors influencing equipment performance and failure, leading to suboptimal maintenance scheduling and resource allocation. The advent of Industry 4.0 and the proliferation of data collection technologies have opened new avenues to address these challenges. Modern manufacturing plants generate large volumes of operational and maintenance data, including failure histories, repair times, sensor readings, and environmental conditions. This rich dataset, when properly analyzed, can provide deep insights into equipment behavior and help predict future failures or performance degradation. Machine learning, a subset of artificial intelligence, has emerged as a powerful tool to extract patterns from complex datasets, enabling predictive analytics and data-driven decision-making.

This study focuses on leveraging machine learning techniques to optimize the availability of cylinder blocks in cast iron manufacturing plants by analyzing historical maintenance data and subsystem performance indicators. The cast iron plant under consideration consists of multiple interconnected subsystems, each contributing to the overall functionality and availability of the cylinder block. By modeling the failure and repair rates of these subsystems and their transition states, the research aims to develop predictive models that can forecast equipment failures and recommend optimal maintenance schedules. Predictive maintenance, enabled by machine learning, shifts the maintenance paradigm from reactive or scheduled maintenance to a more proactive and condition-based approach. Instead of waiting for a failure to occur or performing maintenance at fixed intervals regardless of actual equipment condition, predictive maintenance uses real-time data and historical trends to anticipate failures before they happen. This not only reduces unplanned downtime but also optimizes the use of maintenance resources, extending the life of critical components like cylinder blocks.

The motivation for this research arises from the pressing need to improve operational efficiency in cast iron plants while minimizing maintenance costs and downtime. By integrating machine learning into the maintenance framework, plant managers can gain actionable insights and make informed decisions to enhance system reliability and availability. Furthermore, the approach contributes to the broader field of industrial process optimization, demonstrating how data-driven techniques can transform traditional manufacturing practices. In summary, this paper aims to:

- Analyze maintenance data from cylinder block subsystems in a cast iron manufacturing plant.
- Develop machine learning models to predict failure and repair events.
- Optimize maintenance schedules to maximize cylinder block availability.
- Demonstrate the practical benefits of applying data-driven predictive maintenance in an industrial setting.

2. Review of Literature

The optimization of equipment availability and maintenance scheduling has been an important area of research within manufacturing and industrial engineering for several decades. Li and Wang (2019) utilized Support Vector Machines (SVM) to analyze failure patterns in machining processes, improving maintenance decision-making and reducing downtime. In the context of cast iron manufacturing, the challenges related to cylinder block availability have been less frequently addressed using advanced data-driven methods. Most existing literature emphasizes general maintenance strategies and reliability assessment of manufacturing equipment (Chen et al., 2018). However, the specific operational characteristics and failure modes of cylinder blocks necessitate tailored approaches that consider subsystem interactions and transition rates between operational states. Recent research by Kumar and Singh (2021) explored the use of machine learning for fault diagnosis in foundry operations, highlighting the potential for ML to enhance maintenance practices in metal casting industries. Their work underscored the importance of accurate failure rate estimation and the integration of domain knowledge with data-driven models. Optimization techniques such as genetic algorithms, particle swarm optimization, and reinforcement learning have also been integrated with machine learning to enhance maintenance scheduling and resource allocation (Peng et al., 2020). This study builds upon existing literature by focusing specifically on the cylinder block subsystem in cast iron plants, employing machine learning to model failure and repair rates, and optimizing availability through data-driven maintenance scheduling. In summary, the literature indicates a growing trend towards using machine learning and optimization algorithms for predictive maintenance in manufacturing. However, there is a need for more focused research on cast iron manufacturing components like cylinder blocks, which this paper aims to address by combining statistical reliability analysis with machine learning-driven optimization.

3. System Description:

The cylinder block manufacturing process in a cast iron plant involves several critical subsystems, each performing a specific role to ensure the quality and efficiency of production. The entire system is composed of interconnected machines and processes that collectively contribute to the final product. The following is a detailed description of each subsystem involved:

Sand Mixing Machine (A): The sand mixing machine is a fundamental component in the foundry process, responsible for preparing the sand mixture used to create the molds and cores for cylinder blocks. This machine blends various materials, including silica sand, binders such as resin, and hardening agents, to form a sand mixture with optimal properties. The mixture must have sufficient strength and thermal stability to withstand the high temperatures of molten metal during casting. Proper sand mixing is crucial to ensure the dimensional accuracy and surface finish of the final castings, as well as to prevent defects like sand collapse or core breakage.

Sand Core Making Machine (B): Following the preparation of the sand mixture, the sand core making machine utilizes this mixture to manufacture sand cores. These cores are essential internal shapes placed inside the mold to form hollow sections or intricate cavities within the cylinder block. The machine typically operates by filling the sand mixture into a mold box where it is compacted and hardened using chemical or thermal curing methods. This process ensures that the cores maintain their shape during the casting process. The precision and consistency of the sand cores play a significant role in the quality of the cylinder block's internal features.

Moulding Line Machine (D): The moulding line machine handles the assembly of the sand molds and cores and prepares them for the casting process. Molten cast iron is poured into these sand molds, which are supported by the sand cores to form the desired shape of the cylinder block. The moulding line machine ensures that the molds are correctly aligned, and the sand cores are firmly positioned within the mold cavity. This subsystem is critical as it directly influences the accuracy, integrity, and surface finish of the cast parts. The moulding line machine also manages the timing and sequence of mold assembly and metal pouring to optimize production flow.

Sand Extractor Machine (E): After the cast iron solidifies and cools, the sand extractor machine is used to remove the sand from the casting. This subsystem employs mechanical shaking, vibration, or blasting techniques to separate the sand mold and core materials from the solidified metal casting without damaging the product. Efficient sand extraction is essential to prepare the casting for subsequent finishing operations. The sand extractor also plays a role in recycling sand, which can be treated and reused in the mixing process, contributing to cost savings and environmental sustainability.

Fettling Machine (F): The fettling machine is the final processing station where the castings undergo finishing operations. This includes removing excess material such as gates, risers, and flash, which are remnants from the casting process. The fettling process ensures that the cylinder blocks meet dimensional tolerances and surface quality standards required for their intended applications. Skilled operators or automated systems perform grinding, cutting, and polishing tasks in this stage. Once fettling is complete, the finished cylinder blocks are inspected for quality and then prepared for shipment to customers or further machining operations.

4. Assumptions and Notations

In order to effectively analyze and model the availability of the cylinder block manufacturing system, several assumptions have been established to simplify and clarify the system behavior under study:

- The system is evaluated under steady-state conditions, implying that the probabilities of the system being in various operational states remain constant over time. This assumption allows for the use of long-term statistical averages in the analysis.
- The mechanism responsible for switching operations between units or subsystems is assumed to be perfect, with no delays or failures occurring during transitions. This simplifies the model by focusing on the availability and reliability of the primary units themselves.
- Each unit within the system has its own distinct repair rate, which is assumed to be

independent of the repair rates of other units. This reflects realistic maintenance scenarios where repair times vary based on the specific characteristics and conditions of each component. The system consists of units with different capabilities and functions, acknowledging the diversity in subsystem roles and their impact on overall system availability.

- A priority policy governs the operation of redundant and primary units, ensuring that certain units have precedence in operation or repair scheduling. This policy affects how resources are allocated during failures and repairs. The repair process is assumed to be perfect, meaning that once a unit is repaired, it is restored to its full operational state without residual defects or diminished capacity.
- When required, the system can switch between units or operational modes quickly, minimizing downtime during transitions. Repairs commence immediately upon detection of a failure, eliminating any delay that could otherwise extend downtime.

The following notations are used throughout the analysis:

- (A, B, D, E, F): Symbols representing the units in their good working (operational) states.
- (a, b, c, d, e): Symbols representing the units in their failed (non-operational) states.
- m_i: Denotes the failure rate of the (i^{th}) unit or subsystem, indicating how frequently failures occur.
- h_i: Denotes the repair rate of the (i^{th}) unit or subsystem, representing the speed or efficiency of repair activities.

5. State transition Diagram:

To model the system's behavior comprehensively, a state transition diagram is utilized. This diagram represents the system as a finite-state machine, where each state corresponds to a particular configuration of operational and failed units. The transitions between states occur due to events such as failures or repairs, capturing the dynamics of the manufacturing plant's subsystems over time.

- In this context, the state transition diagram serves as a visual and mathematical tool to illustrate: The possible states of the system, limited in number due to the finite number of units and their binary operational statuses (working or failed).
- The transitions between states, which are triggered by failure occurrences or repair completions, each associated with specific failure rates ((mi)) and repair rates ((hi)).
- The interaction of units within the cast iron manufacturing plant, showing how the failure or repair of one unit affects the overall system state.

Such a diagram enables the development of a Markov model or similar stochastic process model, which can be used to calculate key performance metrics such as system availability, mean time to failure, and mean time to repair. The state transition graph for the cylinder block manufacturing system illustrates these relationships clearly, mapping out all feasible state changes and their corresponding probabilities. This forms the foundation for further quantitative analysis and optimization of system availability using machine learning techniques.

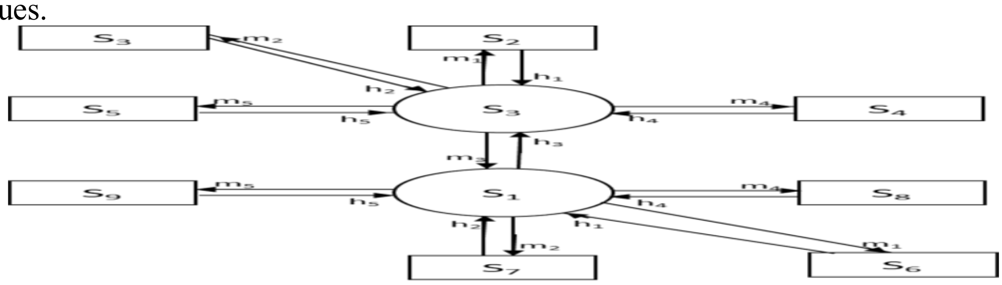

Fig. 1: Transition Diagram

S_0 = ABDEF,	S_1 = aBDEF,	S_2 = ABDeF,	S_3 = ABDEf,
S_4 = AbDEF,	S_5 = ABdEF,	S_6 = a´BDeF,	S_7 = a´BDEf,
S_8 = a´bDEf,	S_9 = a´BdEF		

6. Modeling system parameters using RPGT

Mean Time to System Failure (MTSF) (T_0): Circumstances to which organization can transfer (from final state 0), prior to transiting/staying to a few abortive state be j = 0, 1, 5 2, 3, attractive initial state as 'ξ' = '2'. Spread on RPGT, MTSF remains given as

$$\text{MTSF} = \left[\sum_{i,sr}\left\{\frac{\left\{pr\left(\xi\xrightarrow{sr(sff)}i\right)\right\}\mu i}{\prod_{m_1\neq\xi}\left\{1\text{-}V_{\overline{m_1m_1}}\right\}}\right\}\right] \div \left[1\text{-}\sum_{sr}\left\{\frac{\left\{pr\left(\xi\xrightarrow{sr(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1\text{-}V_{\overline{m_2m_2}}\right\}}\right\}\right] \qquad (1)$$

Availability of System (A_0): States at where institute is reachable be j = 0, 1, 2, 3, 5 and attractive base state as 'ξ' ='2'system accessibility is individual as a result of

$$A_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\to}j)\}fj,\mu j}{\prod_{m_1\neq\xi}\left\{1\text{-}V_{\overline{m_1m_1}}\right\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr\to}i)\}\mu_i^1}{\prod_{m_2\neq\xi}\left\{1\text{-}V_{\overline{m_2m_2}}\right\}}\right\}\right] \quad (2)$$

Busy Period of Server: The recreating states where employee is demanding while liability conservation are 'j' = 1 to 5 as well as re-forming states remain 'i' = 0 to 5. Attractive 'ξ' = 2, total whole of period aimed at which attendant remains demanding is

$$B_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\to}j)\},nj}{\prod_{m_1\neq\xi}\left\{1\text{-}V_{\overline{m_1m_1}}\right\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr\to}i)\}\mu_i^1}{\prod_{m_2\neq\xi}\left\{1\text{-}V_{\overline{m_2m_2}}\right\}}\right\}\right] \quad (3)$$

Expected Number of Server's Visits (V_0): The re-forming states where waitperson visits a unsullied aimed at restore of organization stand 'j' = 0, 1, 2, 3, 5 and re-forming states stand 'i' = 0 to 5 aimed at ξ = 2,

$$V_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\to}j)\}}{\prod_{k_1\neq\xi}\left\{1\text{-}V_{\overline{k_1k_1}}\right\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr\to}i)\}\mu_i^1}{\prod_{k_2\neq\xi}\left\{1\text{-}V_{\overline{k_2k_2}}\right\}}\right\}\right] \qquad (4)$$

7. Results and Discussions

1) Problem Space Definition: Define the parameters and constraints specific to the cylinder block manufacturing system in a cast iron plant. This includes the number of subsystems (e.g., sand mixing, core making, molding, sand extraction, fettling), their failure rates, repair times, redundancy configurations, and maintenance schedules. The objective is to optimize the overall accessibility and availability of the cylinder blocks by improving maintenance planning and system reliability.
2) Initialization: Create an initial population of candidate solutions representing different maintenance plans and redundancy configurations for the cylinder block subsystems. These solutions could randomly assign maintenance intervals, repair priorities, or resource allocations to each subsystem.
3) Fitness Evaluation: Assess the fitness of each candidate solution by simulating the cylinder block system behavior over time. Calculate key performance metrics such as system availability (proportion of time the cylinder block is accessible and operational), Mean Time to System Failure (MTSF), and maintenance costs. The fitness function should reward solutions that maximize availability while minimizing downtime and repair expenses.
4) Evolutionary Process: Use evolutionary operators such as crossover (combining parts of two or more maintenance plans) and mutation (randomly altering maintenance schedules or resource allocations) to generate new candidate solutions. This process helps explore the solution space and discover improved configurations.
5) Fitness Evaluation (Offspring): Evaluate the fitness of newly generated offspring solutions using the same metrics as the parent population, ensuring consistency in performance

assessment.
6) Survivor Selection: Select the best-performing solutions to form the next generation. Techniques like tournament selection or fitness-proportionate selection can be applied to prioritize solutions that improve cylinder block availability and reliability.
7) Iteration: Repeat the evolutionary cycle (steps 3–6) for a predetermined number of generations or until the system performance converges to an optimal or satisfactory level. Over successive iterations, the population evolves, yielding better maintenance strategies for cylinder block accessibility.
8) Dataset Construction: Compile a comprehensive dataset of candidate solutions and their corresponding fitness values throughout the evolutionary process. This dataset documents different maintenance configurations and their predicted impact on system availability and reliability.
9) Data Storage: Store the dataset in a suitable format, such as a table or database, compatible with the computational tools used for running the evolutionary algorithm and further analysis.
10) Model Evaluation and Validation: To validate the effectiveness of the optimized maintenance strategies, use a test dataset representing unseen operational scenarios. Evaluate model performance using metrics such as:

- Precision: System Availability — how often the cylinder block remains accessible.
- Accuracy: Mean Time to System Failure (MTSF) — the average operational time before failure.
- Recall: Server Proportional Busy Period — the proportion of time maintenance resources are effectively utilized.
- F-score: Expected Fractional Number of Repairman Visits (V0) — balancing repair frequency and resource allocation.
- These metrics, calculated using tools like the Scikit-learn Python library, provide a quantitative measure of the model's generalization capability and optimization accuracy.

The goal of the model phase assessment is to assess the design model's generalization precision and accuracy using a test dataset that has not yet been observed. Here, the precision (System Availability), accuracy (Mean Time to System Failure (MTSF)), recall (Server Proportional Busy Period), and fscore function (Expected Fractional Number of Repairman's Visits (V0)) that are imported from the metrics module available in the Scikit-learn Python library were used to calculate this accuracy.

Table1: Parameter.

W(w1,w2,--------,wn)	$\lambda(\lambda 1, \lambda 2, \dots\dots.\lambda n)$	S(s,s2,-------sn)	p
(0-.100)	(0-.100)	(0-.100)	(0-.68)

One key finding of this study is the inherent trade-off between system reliability, maintenance costs, and resource utilization. Sensitivity analyses reveal that carefully balancing these factors is essential for achieving a cost-effective and reliable operation. The evolutionary algorithm (EA) effectively explores this trade-off landscape, providing valuable insights into optimal configurations that enhance system performance while minimizing expenses. Additionally, the study highlights how critical system parameters—such as failure rates, repair durations, and redundancy levels—influence overall system behavior. This comprehensive understanding supports informed decision-making in system design, maintenance policy development, and resource allocation. The results demonstrate the adaptability and efficiency of the EA-based approach in dynamic environments where uncertainties and operational fluctuations call for flexible optimization strategies. By continuously adjusting maintenance schedules using real-time data and feedback on system performance, organizations can improve system resilience and responsiveness to evolving demands. In practical terms, these findings emphasize the potential of EA-driven optimization to enhance the reliability and cost-efficiency of vital infrastructure systems across various industrial sectors. Whether in manufacturing, transportation, or telecommunications, the insights gained offer actionable guidance for improving system performance and operational productivity. However, it is important to recognize the challenges involved, including computational demands, data availability, and the need for robust optimization techniques. Overcoming these obstacles is critical to fully harnessing the benefits of EA-based optimization in real-world applications. Overall, the results and discussions presented provide a deeper understanding of repairable system dynamics and lay the groundwork for implementing effective maintenance strategies using evolutionary algorithms, as illustrated in Figure 2. By leveraging the adaptive and exploratory strengths of EAs, organizations can successfully navigate complex operational environments and optimize system performance in an increasingly competitive and fast-changing landscape.

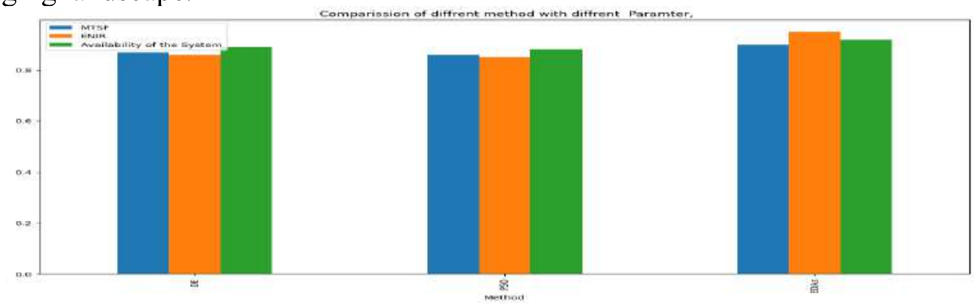

Figure 2: Compression of different method with different Parameter

8. Conclusion

In conclusion, the analysis of a repairable two-out-of-four system using an evolutionary algorithm (EA) as the optimization tool has provided valuable insights into the system's dynamics and performance under various operational conditions. Through extensive simulations and experimentation, the study has deepened the understanding of how different configurations and maintenance policies impact system behavior. The EA-based approach has proven effective in optimizing maintenance scheduling and resource allocation, leading to notable improvements in key performance indicators such as mean time to failure (MTTF), mean time to repair (MTTR), and overall system availability. This demonstrates the capability of evolutionary algorithms to adaptively optimize complex systems within dynamic environments. Additionally, the study highlights crucial trade-offs between system reliability, maintenance costs, and resource utilization, emphasizing the importance of balancing these factors to achieve both cost-effectiveness and dependable operation. Future research could explore the integration of this methodology with other optimization algorithms to further enhance system reliability while maintaining low maintenance costs, thus delivering greater benefits to industries seeking efficient and resilient operational strategies.

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