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DYNAMIC SPARE PARTS INVENTORY MANAGEMENT UTILIZING MACHINE HEALTH DATA

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ABSTRACT

We present a novel approach of utilizing machine health data in order to improve spare parts supply chain performance in a multiple workstation redundancy-based production environment. This research was carried out in collaboration with Augury, an Israeli artificial intelligence company specializing in gathering and analyzing machine health data to improve productivity and profitability. We formulate and solve a new inventory problem that manifests itself with the knowledge of the health-state of machines. We model the system as a continuous time Markov chain. Since finding exact solutions for all but the smallest instances is computationally prohibitive, we address the problem using simulation. We generated and tested a number of Markovian dynamic rules. However, since we are using simulation, we used its flexibility to define and test some non-Markovian rules as well. Both types of rules outperformed the standard optimal base-stock policy. Savings in excess of eighteen percent are observed.

1 INTRODUCTION

In the fast-paced world of industrial production, efficient spare parts inventory management is crucial for maintaining continuous operations. This research, conducted with Augury—an Israeli firm specializing in machine health data—builds on works like those by Shin and Jun (2015), that predicted failures using real-time monitoring thus reducing unexpected downtime, and Lin et al. (2017) who focused on state-dependent spare parts policies on single machine setups. Our research introduces a novel application by integrating machine health data into a dynamic inventory management policy for systems with redundant machines, thereby shifting from the current traditional static framework to a dynamic, data-driven framework.

Effective management of spare parts is vital for reducing downtime and controlling costs, especially in environments where machinery operates continuously. Dual-machine workstations are employed to ensure near-total availability, with one machine actively working and the other one on cold standby—remaining inactive but ready to be powered on when the active machine fails . When a machine fails, the standby is activated, and the failed machine undergoes immediate repair, contingent on the availability of a spare part. Traditional base-stock policies, which maintain a fixed on-hand plus on-order inventory level are often employed without machine health information. However, in the presence of machine health information, static base-stock policies lead to avoidable excess costs or insufficient stock during critical failures.

This study explores how real-time machine health data can improve spare parts management. By classifying machine health into five distinct states—from fully operational to complete failure—inventory levels can be dynamically adjusted based on actual conditions. This proactive approach reduces unnecessary holding costs and improves parts availability for repairs. The research demonstrates that integrating machine health data into inventory management can significantly enhance cost efficiency and operational readiness.

2 MODEL BUILDING

We began by developing a Markov chain model to manage spare parts under a base-stock policy, focusing on the dynamic behavior of workstations and their maintenance needs. The model begins with a single machine, represented by a five-state Markov chain, which describes the machine's operational states and transitions. This model is then expanded to workstations, each comprising two machines with one in a cold standby configuration, in an effort to ensure continuous operation of the workstation. The state of each workstation is represented by an ordered pair of states representing the active and standby machines. Finally, the system-wide model integrates an arbitrary number of these workstations with the inventory status to form a ten-tuple state space that captures inventory levels and machine states. The model aims to minimize total system costs, comprised of inventory holding, major penalty and minor penalty costs. Inventory holding costs arise from maintaining spare parts that are not being used for repairing a machine. Major penalty costs occur when both machines in a workstation fail, leading to significant operational downtime. Minor penalty costs are associated with operating without redundancy, i.e., when exactly one machine at a workstation fails and a repair cannot be initiated due to a lack of spare parts. These costs are calculated over time, as the system transitions through various states.

3 SIMULATION INVESTIGATION AND RESULTS

The Markov chain model faces computational challenges as the number of workstations increases, leading to a unmanageably large state space. To address this, we use simulation techniques to evaluate large systems. Simulation also enables us to investigate inventory policies that do not readily fit into the Markov chain model. The simulation model includes parameters such as the number of workstations, base-stock levels and transition rates, mimicking the system's behavior under various conditions. This allows for the testing of both static and dynamic policies that adjust inventory levels based on machine conditions. Results are validated against the Markov chain model for smaller system instances to ensure accuracy. The following results are observed for a particular system based on real-life data:

- Static Base-Stock Policy: The baseline static policy with a base-stock level of S=3 resulted in a total average cost of 53.48. This policy maintains a fixed inventory level, leading to cost inefficiencies due to either overstocking or shortages.
- Dynamic Policies: Several dynamic policies were tested, where inventory levels were adjusted based on real-time machine health data. For example, one dynamic rule adjusted the base-stock level based on the number of machines in the "imminent failure" state. These dynamic policies resulted in an average cost reduction of approximately 7.7% compared to the baseline static policy.
- Non-Markovian Policies: The most effective dynamic policy adjusted the base-stock level for both excess and lacking inventory independently. It achieved an 18.3% reduction in total average cost.

4 CONCLUSION

This research demonstrates the significant benefits of integrating real-time machine health data into spare parts inventory management. By transitioning from static to dynamic policies, organizations can achieve substantial improvements in cost efficiency and operational readiness. The study provides a robust methodology for implementing these insights in various manufacturing settings, offering a pathway toward more efficient and effective inventory management practices. Future work could expand into multi-echelon supply chains, optimizing inventory across broader networks by integrating real-time machine health data. Additionally, adaptive learning techniques could be employed to refine policies dynamically, improving both forecast accuracy and resource allocation.

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REFERENCES

Shin, J. H., and Jun, H. B. 2015. “On condition based maintenance policy”. *Journal of Computational Design and Engineering* 2(2), 119–127.

Lin, X., Basten, R. J., Kranenburg, A. A., & van Houtum, G. J. (2017). Condition based spare parts supply. Reliability Engineering & System Safety, 168, 240–248.