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Spare Part Inventory Control in a Condition-Based Maintenance Context: A Proactive Policy

N. Al Khoury[1,2], D. Fiems[3], E-H. Aghezzaf[1,2], D. Claeys[1,2]
[1] *Ghent University, Department of Industrial Engineering and Product Design, Gent, Belgium, naim.alkhoury@ugent.be*
[2] *Industrial System Engineering (ISyE), Flanders Make, Belgium*
[3] *Ghent University, Department of telecommunications and Information Processing, Gent, Belgium*

Managing spare parts inventory is a vital task for striking a balance between availability and operating costs. Given the substantial costs involved, this topic has garnered considerable interest in both industrial and scientific communities [1]. In the literature, two research communities are working on the problem. One entails the development of forecasting methods that extrapolate future spare parts demand, and the other focuses on developing decision-making methods to prescribe spare parts procurement. These techniques incorporate historical and real-time data to identify optimal solutions. Condition Based Maintenance (CBM) represents a maintenance strategy aimed at performing maintenance precisely when it is required. With the advances in sensors and communication technologies, there is an increasing focus on developing methods to exploit real-time information to predict functional failures and prescribe appropriate actions accordingly. A prevalent approach involves the adoption of a threshold policy wherein part replacement is initiated when degradation surpasses a predefined threshold [2, 3]. Implementing CBM promises significant cost savings. As a result, it is an active area of research, and major commercial companies are developing software to benefit from condition information. The use of condition information in spare parts decision-making is also a growing trend. However, it has not reached its full potential. Therefore, we propose a Proactive Base Stock (ProBSP) policy where we incorporate real-time degradation data in the spare parts decision-making process. We develop a model with multiple machines, general degradation processes, and stochastic lead times. Spare parts are ordered proactively every time a machine surpasses an ordering threshold. To meet demand, an initial stock of spare parts is necessary. Consequently, the ProBSP policy involves the management of two key control parameters: the initial stock level and the order threshold. We develop a simulation-based optimization method to compute the optimal control parameters of the policy. First, the performance of the ProBSP for a given set of parameters is evaluated using Discrete Event Simulation (DES). Then, an intelligent search algorithm is constructed which exploits the structural properties of the policy to find the optimal parameters. We then compare the potential savings to the case when inventory is managed using a Base Stock Policy (BSP). This extensive numerical experiment considers different numbers of machines, different degradation scales and behavior over time, and diverse lead time distributions. The ProBSP achieves on average 68% savings compared to the BSP, and savings are higher than 90% in some scenarios. Additionally, the ProBSP is robust with a varying number of machines, which is important for practitioners as they have regular changes in their customer base.

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