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Real-time integrated learning and decision making for cumulative shock degradation

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Problem definition: Unexpected failures of equipment can have severe consequences and costs. Such unexpected failures can be prevented by performing preventive replacement based on real-time degradation data. We study a component that degrades according to a compound Poisson process and fails when the degradation exceeds the failure threshold. An online sensor measures the degradation in real time, but interventions are only possible during planned downtime.
Academic/practical relevance: We characterize the optimal replacement policy that integrates real-time learning from the online sensor. We demonstrate the effectiveness in practice with a case study on interventional x-ray machines. The data set of this case study is available online. As such, it can serve as a benchmark data set for future studies on stochastically deteriorating systems.
Methodology: The degradation parameters vary from one component to the next but cannot be observed directly; the component population is heterogeneous. These parameters must therefore be inferred by observing the real-time degradation signal. We model this situation as a partially observable Markov decision process (POMDP) so that decision making and learning are integrated. We collapse the information state space of this POMDP to three dimensions so that optimal policies can be analyzed and computed tractably.
Results: The optimal policy is a state dependent control limit. The control limit increases with age but may decrease as a result of other information in the degradation signal. Numerical case study analyses reveal that integration of learning and decision making leads to cost reductions of 10.50% relative to approaches that do not learn from the real-time signal and 4.28% relative to approaches that separate learning and decision making.
Managerial implications: Real-time sensor information can reduce the cost of maintenance and unplanned downtime by a considerable amount. The integration of learning and decision making is tractably possible for industrial systems with our state space collapse. Finally, the benefit of our model increases with the amount of data available for initial model calibration, whereas additional data are much less valuable for approaches that ignore population heterogeneity.

Keywords: Maintenance, Bayesian learning, Replacement, Optimal policies, Markov decision process