Computers & Industrial Engineering 120 (2018) 471–479

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Capacitated inspection scheduling of multi-unit systems

Esra Sisikoglu Sir[a], Mahmood Pariazar[b], Mustafa Y. Sir[a,*]

[a] Mayo Clinic, Rochester, MN, United States
[b] American Airlines, Fort Worth, TX, United States

ARTICLE INFO

Keywords:
Scheduling
Inspection and maintenance
Approximate dynamic programming
Multi-unit systems

ABSTRACT

We consider the inspection scheduling problem of multi-unit systems where the inspections of individual units are coupled via a capacity constraint. Although the optimal inspection policy of the majority of single-unit systems can be characterized by a threshold policy, finding an optimal policy for multi-unit systems is significantly harder. Therefore, the current state-of-the-practice uses a periodical inspection policy for all units. Instead, we propose using a dynamic programming (DP) approach to solve small-scale problem instances to optimality and use solutions optimized for a single-unit system in an approximation scheme to obtain near-optimal solutions for large-scale problems. Our results show that taking individual properties of the units to be inspected into account and incorporating the single-unit solutions within an approximate DP framework significantly decrease the inspection cost compared to a periodical inspection policy. The proposed methods can help resource-constrained regulatory agencies such as US Food and Drug Administration (FDA) to optimize their inspection activities.

1. Introduction

Inspection and maintenance scheduling of multi-unit systems under limited budget have important applications in various industries such as pharmaceutical and food supply chains, transportation, and manufacturing. For some of these industries, lack of or poorly planned inspection activities could involve significant risks. For example, in 2008, 81 people died due to use of tainted Heparin, a widely used anticoagulant medicine. This unfortunate event initiated a heated debate on quality practices in drug manufacturing and the need for stricter inspection regulations in the pharmaceutical industry (Gardiner, 2008). The current state of the practice mandates inspection of all pharmaceutical suppliers every two years (Klimberg, Revelle, & Cohon, 1992). As a result, FDA had to increase its inspection budget to afford more frequent inspection-related activities (FDA, 2014; Palmer, 2013). Other examples in which human lives are put at risk due to ineffective inspection policies include transportation networks and food supply chains. Effective inspection of traffic signs and lights, roads, and critical infrastructure such as bridges in a transportation network are of crucial importance as the deterioration in the condition of any of these components can have devastating consequences (Chen, 2017; Galambos, 2008). Similarly, inability to timely detect contaminated products in food supply chains could cause salmonella outbreaks and pose a risk to public health (Aung & Chang, 2014). Therefore, effective and efficient planning of inspection and corrective maintenance activities in such multi-unit systems is of great importance.

Our aim in this paper is to develop a mathematical model to find optimal inspection schedules in a system consisting of multiple units (e.g., suppliers in a pharmaceutical network or critical infrastructure such as bridges within a transportation network) over a long planning horizon. The condition of each unit stochastically changes with a unique degradation probability distribution and an associated cost. The decision maker, who is responsible for inspecting and, if necessary, maintaining each unit on a continuous basis, has limited resources for these activities.

Inspection of pharmaceutical supply chains provides a motivating example for our model. One interesting aspect of this problem is that the cost of shipping a tainted drug to health care providers is very high as it may result in fatalities. Moreover, it may take a very long time before the adverse effect of a tainted drug is realized, and a causal relationship between the adverse events (e.g., fatalities) and the tainted drug is established. Therefore, we define the state of each unit (e.g., pharmaceutical supplier) to be either “in-control”, supplying high-quality products, or “out-of-control”, supplying tainted products. Because it typically takes a long time to realize the adverse effects of a failure event causing a unit transition into an out-of-control state, we assume that the true state of a unit can only be known through inspection. If we find a unit to be out-of-control as a result of an inspection, the unit undergoes certain maintenance activities to ensure that it will be in-control in the subsequent period.

* Corresponding author.
E-mail addresses: sir.esra@mayo.edu (E. Sisikoglu Sir), Mahmood.Pariazar@aa.com (M. Pariazar), sir.mustafa@mayo.edu (M.Y. Sir).

https://doi.org/10.1016/j.cie.2018.04.022
Received 8 March 2017; Received in revised form 23 March 2018; Accepted 11 April 2018
Available online 24 April 2018
0360-8352/

The goal is to find an inspection scheduling policy that minimizes the overall cost, composed of the costs of inspection, maintenance, and missed detection of an out-of-control unit, over a long planning horizon. The costs across units might vary. Inspection cost depends on whether it is done using in-house resources or outsourced. Maintenance cost includes the cost of all activities performed to rectify an out-of-control unit back to an in-control condition. Other costs such as salvage cost and the cost of unsatisfied demand can also be included as part of the maintenance cost. The cost of missed detection of an out-of-control unit may include the cost associated with fatalities due to tainted products reaching customers and any related lawsuits. For example, in the Heparin case, tainted heparin produced by an out-of-control drug manufacturer may cause harm to patients. This cost may also include the cost of returned defective products and loss of trust between different suppliers within a multi-tier supply chain.

We also assume that there is a limit on the number of inspections that can be performed in a given period. This assumption can easily be relaxed for those situations where there is a budget limit on the amount of inspection-related expenses in a given period. Due to this capacity limit, it may not be possible to inspect every unit periodically. Furthermore, these types of periodic inspection scheduling policies may not represent the best use of resources. Certain units with a higher degradation probability (e.g., drug manufacturers without quality improvement programs) may need more scrutiny. Other units with a lower degradation probability (e.g., high-quality drug manufacturers) can be inspected less frequently.

A dynamic inspection scheduling strategy can allocate limited inspection budget to different units over a long planning horizon optimally considering individual degradation probability distributions, the latest inspection results from the earlier periods, and various costs. Therefore, we model this problem using a dynamic programming (DP) framework (Puterman, 1994). It is a well-known fact that, for large-scale problems (in our case, systems with a large number of units), DP algorithms can quickly become intractable (Powell, 2007). As presented in the numerical results section, the proposed DP model with more than four units cannot be solved within a reasonable time limit when the value iteration algorithm, a very well-known DP solution method (Bertsekas, 1995), is applied. Therefore, we develop approximation strategies to find near-optimal solutions for inspection problems having a large number of units to be inspected. Based on numerical results and analysis, the optimal solution can be easily characterized when the system to be inspected involves a single unit. Using the optimal solution of a single-unit model, we propose an approximation scheme where the value function of the original multi-item problem is approximated (see Section 3 for details). Numerical results show that our proposed approximation scheme produces high-quality near-optimal solutions with significant performance improvements over periodic inspection policies.

Our research has many common aspects with machine replacement and maintenance optimization literature. Machine replacement research was initiated in the 50's and 60's with a focus on problems involving a single machine and two feasible actions: repair (replace) or do nothing (Derman, 1963). Earlier studies focused on characterizing the structure of optimal maintenance policies using Markovian deterioration models to describe the change in the unit's condition over several periods (Kolesar, 1966; Ross, 1967). Later, these models were extended to include inspection decisions to reveal the actual state of the machine (Ross, 1971; Rosenfield, 1976). Several structural results characterizing the optimal timing of when to inspect and repair have been proven. Rosenfield (1976), for example, investigated the value of obtaining information about the condition of a single unit via inspection by considering several feasible actions including "inspect", "repair" and "no action." He showed that the optimal policy has a special structure, in which the state space is divided into at most four regions, in each of which, a single action is optimal. Later, these studies were generalized to the inspection and replacement of a single-unit system by relaxing various assumptions on the cost structure, deterioration model, and maintenance strategies (Hopp & Wu, 1990; Lam & Yeh, 1994). In later years, the machine replacement problem was generalized to multiple stochastically deteriorating machines (McClurg & Chand, 2002; Moghaddam & Usher, 2011). The optimal replacement policy in these problems is generally characterized by "no splitting" or "worse cluster replacement" rules. The basic idea is that if it is optimal to replace a machine in a particular condition than it is optimal to replace all machines having the same or worse condition. Even though such results are insightful, these models fail to capture many important aspects of many real-world problems, such as limited budget allocated for machine replacement in each decision period.

Maintenance optimization problems have also been extensively studied, with numerous surveys detailing this work (Garg & Deshmukh, 2006; Nicolai & Dekker, 2008; Sharma, Yadava, & Deshmukh, 2011). They are generally classified based on whether the degradation of the system is modeled in continuous (Dieulle, Berenguer, Grall, & Roussignol, 2003) or discrete time (Amari & McLaughlin, 2004; Tamura, 2007); if the system is composed of a single unit (Crespo Marquez & Sánchez Heguedas, 2002; Valdez-Flores & Feldman, 1989) or multiple units (Nicolai & Dekker, 2008; Wang, 2002); and whether maintenance activities restore the unit condition to the best possible ("like-new" or "perfect") level (Grall, Berenguer, & Dieulle, 2002) or not (Pignal, 1987; Rangan & Grace, 1989). Our model is most related to the discrete-time maintenance optimization models with multiple units and perfect maintenance as, in our model, we assume that if a unit is found to be "out-of-control" in the current period, its condition is restored to be "in-control" in the subsequent period via possibly some maintenance activity.

Several scheduling policies have been proposed for maintenance of multiple units including age-based (Scarf, Cavalcante, Dwight, & Gordon, 2009), condition-based (Camci, 2009; Tian & Liao, 2011), group maintenance (Sheu & Jhang, 1997), and block replacement policies (Sheu, 1991). For example, Ritchken and Wilson (1990) proposed a group maintenance policy in which an entire group of units receives maintenance when a certain fraction of those units fail or reach a certain age. Sheu and Jhang (1997) generalized the group maintenance policy by classifying failures into two types (minor and catastrophic) and divided the lifetime of a unit into two phases so that different policies could be assigned to different phases. In particular, their maintenance policy allows minimal repairs for minor failures throughout the lifetime of the unit whereas, in case of a catastrophic failure, it either replaces (in early phases of a unit's lifetime) or leaves the unit idle (in later phases). Sheu (1991) proposed a block replacement policy that replaces the system periodically and repairs it after a failure. In a closely related work, Grigoriev, van de Klundert, and Spieksma (2006) proposed several integer programming formulations for a periodic maintenance problem of multiple machines, each having a specific servicing cost. Their model allows only one machine to be serviced in a given period and the operating cost of each machine is a linear function of time since the last servicing. Kuschel and Bock (2016) also proposed an integer programming formulation that optimizes the total cost of system maintenance by optimizing the scheduling of a predetermined set of maintenance activities over a finite planning horizon. Their model does not take into account stochastic degradation of system components. Gustavsson, Patriksson, Strömberg, Wojciechowski, and Önnheim (2014) proposed a different integer programming based formulation to optimize scheduling of preventive maintenance activities considering deterministic degradation functions.

In contrast to studies reviewed above, in our model, there is a capacity limit on the maximum amount of inspections that can be performed in a decision period. Also, each unit has a different degradation probability distribution and associated cost. Decisions of which units to inspect in each period are made dynamically by considering the state of each unit instead of a static policy that assumes the same decision for a group of units. Moreover, because of the capacity limit on the