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Decision Support

Maintenance scheduling of geographically distributed assets with prognostics information

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ABSTRACT

Maintenance scheduling for high value assets has been studied for decades and is still a crucial area of research with new technological advancements. The main dilemma of maintenance scheduling is to avoid failures while preventing unnecessary maintenance. The technological advancements in real time monitoring and computational science make tracking asset health and forecasting asset failures possible. The usage and maintenance of assets can be planned more efficiently with the forecasted failure probability and remaining useful life (i.e., prognostic information). The prognostic information is time sensitive. Geographically distributed assets such as off-shore wind farms and railway switches add another complexity to the maintenance scheduling problem with the required time of travel to reach these assets. Thus, the travel time between geographically distributed assets should be incorporated in the maintenance scheduling when one technician (or team) is responsible for the maintenance of multiple assets. This paper presents a methodology to schedule the maintenance of geographically distributed assets using their prognostic information. Genetic Algorithm based solution incorporating the daily work duration of the maintenance team is also presented in the paper.

1. Introduction

Today's highly competitive environment pressurizes industry for continuous cost reduction. Maintenance research has been attractive to researchers and industry in recent years because asset maintenance and repair significantly contribute to operation and support costs (Camci & Chinnam, 2010). In addition, maintenance is not a standalone operation, as it interacts with many other operations, such as production planning, inventory management, and personnel within the business, creating great complexity (Nourelfath & Châtelet, 2012).

Predictive maintenance proposes to maintain assets only when necessary in the right time, aiming to reduce unnecessary maintenance by monitoring and forecasting asset health. The term asset represents any system that is monitored for maintenance.

In predictive maintenance, the health of the asset is observed in operating time by analyzing signals that have been collected from sensors that are embedded in the assets. The process of detecting an existing incipient failure, called diagnostics, and the process of forecasting the time of the failure and identification of the remaining useful life (RUL) of the asset before failure occurs, called prognostics, are the two major steps in predictive maintenance (Camci & Chinnam, 2006; Eker et al., 2011; Jardine, Lin, & Banjevic, 2006). Maintenance may be scheduled immediately for an asset when an incipient failure is diagnosed. However, the asset with an incipient failure or some level of degradation can still be used until the complete failure. Identification of the time of the complete failure creates an opportunity for effective maintenance planning. The asset is expected to perform according to its typical functionality, but possibly less efficiently, within the identified RUL. Prognosis of a failure identifies the remaining useful life of the asset for effective maintenance planning and preparation.

In predictive maintenance research, the RUL may be time (e.g., 3 months to failure) or operational working period (e.g., 3000 miles of driving before failure) and is defined by setting a threshold value to a given parameter such as efficiency decrease or failure probability (Barbera, Schneider, & Kelle, 1996; Berenguer, Grall, Dieulle, & Roussignol, 2003; Marseguerra, Zio, & Podofillini, 2002; Sloan & Shanthikumar, 2002; Yam, Tse, Li, & Tu, 2001). In these cases, maintenance is performed when the parameter reaches the given threshold.

Even if the optimization of the threshold for prognostics information may be sufficient for some systems, it is not sufficient for maintenance scheduling of geographically distributed assets. Railway switches and wind turbines in wind farms are two examples of geographically distributed assets. The travelling cost for maintenance and the effects of travelling time on the probability of failure should be incorporated for effective maintenance scheduling of geographically

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Notation

C^F	total expected failure cost
C^M	total maintenance cost
C^T	total travel cost
n	number of distributed assets
T	maintenance schedule time period
$P_{i,t}$	cumulative failure probability of asset i on day t
P_P	expected failure probability progression if the system is left as it is without maintenance
$P_{P,t}$	failure probability obtained from prognostics at time t
P_R	expected failure probability progression after a maintenance
$P_{R,t-LM}$	failure probability obtained from reliability analysis at $(t - LM)$ time units after a maintenance
DT_i	expected downtime when a failure occurs in asset i
δ_i	downtime cost per unit time for asset i
F_i	direct failure cost
γ_i	fixed maintenance cost for asset i
c_d	travel cost of unit distance
c_γ	cost increase per each time unit in fixed maintenance cost when work duration exceeds D_w
π_i^t	city order (asset number visited in the ith order at time t)
$d_{\pi_{i-1}^t,\pi_i^t}$	distance between assets visited π_{i-1}^tth order and π_i^tth order
$TT(d_{\pi_n,\pi_0})$	travel time of distance d_{π_n,π_0}
t_i^r	maintenance duration for the asset i
LM	time of last maintenance
M_t	number of assets to be visited at time unit t
D_w	working duration for maintenance in a time unit
D_w^{up}	upper limit for the work duration in a time unit
$x_{i,t}$	1 if asset i is scheduled for maintenance at time t; 0 otherwise
ε_i	random number for asset i for ranking the visit order
θ_i	string of binary numbers with $log_2(T+1)$ binary numbers representing the maintenance times for asset i in the given period $(b_{log_2(T+1)} \dots b_2 b_1)$

distributed assets. For example, consider an off-shore wind farm with many wind turbines located in the middle of the sea. Assume that one of the wind turbines is scheduled for maintenance next week based on the threshold set for prognostics information. Should the wind turbines located close to the one scheduled for maintenance be maintained before coming back to the shore? If the maintenance operations for two wind turbines are scheduled consecutively, will it be possible for the technicians to be at the assets at their scheduled times considering the travel times?

This paper presents a formulation for the maintenance scheduling of geographically distributed assets to answer these types of questions by incorporating failure, maintenance, and travel costs in the same formula and a Genetic Algorithm (GA) based solution. GA is a widely used approach to approximate the global optimum for nonlinear problems and especially attractive in scheduling problems with binary representation power (Marseguerra et al., 2002). The contribution of the presented methodology is to increase the applicability of the presented problem to real systems with high numbers of assets and to incorporate work duration for maintenance operators in the formulation.

Section 2 gives the literature review, Section 3 presents the problem formulation, and Section 4 presents methodology to solve the problem. Section 5 demonstrates case studies, and Section 6 concludes the paper.

2. Literature review

Maintenance scheduling has been extensively studied in the past. The maintenance concept can be considered in three categories: corrective maintenance, periodic maintenance, and predictive maintenance (Camci & Chinnam, 2010). Corrective maintenance is a reactive action of repairing the assets after the failure. Periodic maintenance aims to avoid failure by periodic maintenance. Predictive maintenance focuses on early detection and forecasting of failures through condition monitoring techniques.

The majority of the early studies have focused on the optimization of the maintenance period. Because this paper is concerned with maintenance scheduling in predictive maintenance, studies about periodic maintenance scheduling will not be discussed. Reference Ben-Daya, Duffuaa, and Raouf (2000) reviews the early studies on maintenance scheduling.

Group maintenance aims to group the components based on their functionalities, spacial closeness in the system, expected life times, and other properties (Gertsbakh, 1984; Sheu & Jhang, 1997). When one of the components fails or needs maintenance, the whole group is replaced or maintained. This grouping is performed using the components of one system (Levrat, Iung, Macchi, Thomas, & Voisin, 2011; Thomas, Levrat, & Iung, 2008; Van, Florent, Keomany, Barros, & Berenguer, 2011; Van, Vu, Barros, & Berenguer, 2012). Opportunistic maintenance aims to identify possible preventive maintenance options when the system stops due to failure or the need for maintenance of one component (Dagpunar, 1996; Nakagawa & Murthy, 1993). The inter-relation between opportunistic maintenance and mission planning or the job shop schedule depending on the asset types have been studied for further cost reduction (Zhou, Lu, & Xi, 2012). These approaches are based on failures that have already occurred and on scheduled maintenance.

The usage of RUL information for maintenance scheduling and mission planning has been reported in Li, Ambani, and Ni (2009), Papakostas, Papachatzakis, Xanthakis, Mourtzis, and Chryssolouris (2010), Sandborn and Wilkinson (2007). The aforementioned threshold setting on the estimated RUL is the general approach in predictive maintenance. The optimization of the threshold value for the RUL is studied in reference Marseguerra et al. (2002). The problem of the static threshold is discussed and a dynamic threshold concept is presented in reference Li, You, and Ni (2009). However, it is clearly demonstrated in references Camci (2009a, 2009b) that the threshold setting for RUL will not always provide the best maintenance scheduling, especially for systems with multiple dependent components.

Several studies exist that aim to obtain an effective maintenance schedule without an RUL threshold setting. Zhang et al. has used semi-Markov models to represent the deterioration of roads for maintenance planning (Zhang & Gao, 2012). You et al. presents a maintenance management tool for a batch of single-unit systems by incorporating past statistical information and failure predictions of individual systems (You, Liu, Wang, & Meng, 2010). Multi-objective optimization has been used in Wang and Pham (2011) for the maintenance policy of a single-unit system. However, none of these studies aim to address geographically distributed assets. This paper aims to schedule the maintenance based on the analysis of RUL values of geographically distributed assets and the travel distances between them.

The Travelling Repairman Problem (TRP) discussed in the literature addresses repair scheduling of distributed assets (Fakcharoenphol, Harrelson, & Rao, 2003; Garcia, Jodra, & Tejel, 2002; Irani, Lu, & Regan, 2004; Jothi & Raghavachari, 2007). Although the name “repairman” evokes the problem presented, the nature of the