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A framework to practical predictive maintenance modeling for multi-state systems

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Abstract

A simple practical framework for predictive maintenance (PdM)-based scheduling of multi-state systems (MSS) is developed. The maintenance schedules are derived from a system-perspective using the failure times of the overall system as estimated from its performance degradation trends.

The system analyzed in this work is a flow transmission water pipe system. The various factors influencing PdM-based scheduling are identified and their impact on the system reliability and performance are quantitatively studied. The estimated times to replacement of the MSS may also be derived from the developed model.

The results of the model simulation demonstrate the significant impact of maintenance quality and the criteria for the call for maintenance (user demand) on the system reliability and mean performance characteristics. A slight improvement in maintenance quality is found to postpone the system replacement time by manifold. The consistency in the quality of maintenance work with minimal variance is also identified as a very important factor that enhances the system's future operational and downtime event predictability.

The studies also reveal that in order to reduce the frequency of maintenance actions, it is necessary to lower the minimum user demand from the system if possible, ensuring at the same time that the system still performs its intended function effectively.

The model proposed can be utilized to implement a PdM program in the industry with a few modifications to suit the individual industrial systems' needs.

Keywords: Maintenance quality; Markov chain analysis; Multi-state system (MSS); Restoration factor (RF); Time to replacement (TTR); Time to failure (TTF); Universal generating function (UGF); User demand

1. Introduction

Maintenance has evolved from the age-old ad hoc corrective (or reactive) maintenance [1] (CM) to preventive maintenance (PM) [2] and then to the presently popular predictive maintenance (PdM) [3,4] because both the CM and PM are well recognized as ineffective. In the case of CM, the "completely failed" system is highly degraded, making maintenance very difficult, time-consuming and expensive. Also, CM is associated with large and unpredictable downtimes resulting in low mean availability and increased forgone production losses. As for PM, the fixed downtime intervals would imply more-than-necessary repair frequency during the initial periods of the system operation that could increase the probability of maintenance-induced failures. On the other hand, as the system ages and enters into its wear-out period, PM results in less-than-necessary repair frequency, thereby increasing the probability of unanticipated catastrophic failures and making PM similar to CM.

In PdM, which is also referred to as a condition-based PM [5], the maintenance schedule and frequency match the age or health of the system at all times, making the schedule nearly optimum, prolonging the time to replacement (TTR) as a consequence. The expected times to future failure of a system are estimated during each operational period based on the variation pattern

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of its physical properties (condition monitoring) that are indicative of its state of degradation using implanted sensors, and the downtime schedule for each operation cycle is determined based on the estimated future failure times. Past research studies show that the average system reliability (and yield), availability and mean system performance are the highest for PdM and the incurred maintenance operation costs are the lowest [6]. The spare part requirements and delay times are also reduced due to reliable prior predictions of future downtime events.

However, there are currently two main obstacles to the practical implementation of the PdM policy. Firstly, there is no simple concrete statistical model that PdM can be based upon. The past models developed are theoretical in their approach with idealistic assumptions and fitting parameters, rendering them unfit for practical real-world implementation. For example, in [7], it was proposed that the system being repaired could be restored to either the "as-good-as-new" condition or the "as-bad-as-old" condition with complementary probabilities, failing to account for the possibility that the system's restoration could be somewhere in between these two possible extreme cases. Although the *virtual age* model proposed by Kijima [8] to account for the imperfect restoration helped overcome the above-mentioned problem, the determination of the effective age parameter "a" in the proposed model is not given, making its implementation vague.

Secondly, the implementation of PdM requires advanced monitoring technologies, real-time data acquisition systems with sophisticated data storage and speed requirements and signal processing techniques [9], making the implementation of PdM complex and expensive. However, with the advances in sensor technologies today, this difficulty is gradually overcome [10].

In this work, we will focus on the first obstacle which is to develop a comprehensive and practical statistical model for PdM. *Imperfect maintenance* will be considered in this work for practical applications. This imperfect maintenance is a term frequently used to refer to maintenance activities in which the future reliability and degradation trend of the system depends on the skill and quality of the current and previous repair works performed. In other words, imperfect maintenance accounts for the impact of maintenance quality, due to maintenance personnel skill and spare part quality, on the future reliability of repairable systems.

The structure of this paper is as follows. Section 2 gives a brief review on the various existing models for imperfect maintenance. Section 3 introduces the methodology for the multi-state systems (MSS) PdM modeling and the description of the system case study. Section 4 describes the various results from the model simulation and Section 5 discusses the limitations to be overcome. Finally, a short summary of the work done and results achieved is presented in Section 6.

2. Imperfect maintenance

Various models have been proposed for imperfect maintenance in the past from different perspectives as reviewed in complete detail in [11]. Basically, there are four classes of models developed so far.

The first class of models was based on a *probabilistic approach* [12–14] where it was assumed that the system undergoes "perfect renewal" to "as-good-as-new" condition with a constant probability of p and "minimal repair" to "as-bad-as-old" condition with a probability of $(1-p)$. Further enhancement to this probabilistic approach was to consider the probabilities as time-varying functions, $p(t)$ and $[1-p(t)]$, to account for the change in these values with the aging system's degradation [15,16]. Makis and Jardine [17] further account for the probability that the repair is unsuccessful and causes a catastrophic complete system failure and the $p(t)$ function was modified to $p(n,t)$ to describe the probability accounting for the number of previous failures, n, undergone by the system prior to the current one.

The second class of models was based on the *improvement factor* method where the system was analyzed by looking at the failure rate. Certain models were proposed to reflect the reduction in failure rate after repair [18,19]. The degree of improvement in the failure rate was called improvement factor and "failure rate" was used as the threshold reliability index.

The third class of models was based on the age of the system. The most popular model in this class is known as the *virtual age model* proposed by Kijima et al. [8,20]. The virtual age of the system after the nth repair (V_n) is expressed as: $V_n = V_{n-1} + a \cdot X_n$ where X_n is nth failure time, V_{n-1} is the virtual age after $(n-1)$th repair and "a" is the virtual age parameter ($0 \leqslant a \leqslant 1$). However, the method of estimating the parameter "a" is not mentioned in the literatures. Another age-based model called the *proportional age setback model* was proposed in [21] which is very similar to the virtual age model, except that the effects of equipment working conditions and surveillance effectiveness on imperfect maintenance and corresponding age reduction are accounted for in addition to the maintenance work quality.

The fourth class of models was based on the *system degradation* where the system is considered to suffer random shocks at variable intervals of time causing it to undergo progressive increments of damage [22,23]. When a threshold cumulative damage level is reached, the system is interpreted to have failed. The effect of the imperfect maintenance actions is described by the degree of reduction of the cumulative system damage after repair as compared to that before repair. Wang et al. [24–27] treated imperfect maintenance by modeling the decrease in system lifetime with the increase in the number of repairs. They also modeled the time between maintenance actions using a quasi-renewal process [26].