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A model for preventive maintenance planning by genetic algorithms based in cost and reliability

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Abstract

This work has two important goals. The first one is to present a novel methodology for preventive maintenance policy evaluation based upon a cost-reliability model, which allows the use of flexible intervals between maintenance interventions. Such innovative features represents an advantage over the traditional methodologies as it allows a continuous fitting of the schedules in order to better deal with the components failure rates. The second goal is to automatically optimize the preventive maintenance policies, considering the proposed methodology for systems evaluation.

Due to the great amount of parameters to be analyzed and their strong and non-linear interdependencies, the search for the optimum combination of these parameters is a very hard task when dealing with optimizations schedules. For these reasons, genetic algorithms (GA) may be an appropriate optimization technique to be used. The GA will search for the optimum maintenance policy considering several relevant features such as: (i) the probability of needing a repair (corrective maintenance), (ii) the cost of such repair, (iii) typical outage times, (iv) preventive maintenance costs, (v) the impact of the maintenance in the systems reliability as a whole, (vi) probability of imperfect maintenance, etc. In order to evaluate the proposed methodology, the High Pressure Injection System (HPIS) of a typical 4-loop PWR was used as a case study. The results obtained by this methodology outline its good performance, allowing specific analysis on the weighting factors of the objective function.

Keywords: Maintenance policy optimization; Genetic algorithms; Cost-reliability model

1. Introduction

In a Nuclear Power Plant (NPP) Pressurized Water Reactor (PWR), the maintenance policy applied to the electrical-mechanical systems, due to the high level of reliability of these components, requires an optimized schedule. A high maintenance intervention frequency, as often recommended in factory specifications, however, it should sometimes represent unnecessary costs, which may not correspond to an increase on the components reliability. Besides, the factory recommendation for maintenance policies does not consider the aging of the component, which affect its operational condition.

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On the other hand, according to Duffey [9], in a 4-loop PWR NPP, the maintenance costs during its lifetime represents about 30% of the total operation cost of the NPP. Hence, a little enhancement in the maintenance polity may proportionate a significant economical gain. Considering such arguments, this work is intended to develop a methodology to preventive maintenance policy optimization, which deals with operational, economical and safety aspects, providing an advanced methodology based upon a probabilistic cost-reliability model and a powerful optimization technique.

According to Duthie et al. [8], since the beginning of the last decade, researchers have been publishing papers addressing preventive maintenance optimization of nuclear power plant systems. This may be classified in three main groups. The first one has the focus on system's reliability [12,32]. The second one focuses on probabilistic models and perform tests among some standard policies [8,24]. Finally, we can mention those, which apply expert knowledge to determine good maintenance policies [31]. In order to avoid the optimization difficulties inherent to huge search spaces, many applications have considered systems with few components [2,11].

From the probabilistic point of the view, Park et al. [26] contributed to the solution of the class of problem under discussion by including components with very small degradation degrees, Chiang and Yuan [6] have proposed approaches for maintenance optimization problems aiming at obtaining system's availabilities by Markovian methods and Dijkhuizen and Heijen [7] have optimized the distribution of availability intervals instead of optimizing the preventive maintenance policy.

Unfortunately, all the mentioned references have a common feature: they all considered systems composed by a few components and even so they faced difficulties from the point of view of optimization. By the other side, it is well-known that safety-related nuclear systems have many redundancies and components with a great number of combination and alignment alternatives among them. So, in this case others approaches are necessary to deal with such complexity.

Muñoz et al. [23] were the first ones that have proposed the use of genetic algorithms (GA) [13] as an optimization tool for maintenance scheduling activities. Lapa et al. [14–16] applied GA in order to optimize inspection and maintenance intervals with a new approach. Instead of searching for an optimal intervention frequency, which means equally spaced interventions, they employed the optimization tool to search for the times in which preventive maintenance interventions should be performed (Flexible Interval Method—FIM). In this sense, it is understood that equally spaced intervention actions do not necessarily lead to the optimal policy.

Recently, Yang et al. [33] proposed a test surveillance policy optimization on the plant level. Test surveillance policy optimization has also been investigated by Lapa et al. (2001) [17,18]. This methodology has been successfully applied by Lapa et al. [20] in optimization problems that into account constraints in the search space. We need also to mention Bris et al. [3] research, in which they have developed a new approach to maintenance optimization based in cost. Recently, a important work outlining alternatives and challenges in optimizing industrial safety using genetic algorithms have been developed by work Martorell et al. [25].

2. Probabilistic modeling

In this section, we present models that calculate both the reliability of a component and the individual cost per component while submitted to a given maintenance schedule.

2.1. The reliability model for preventive maintenance scheduling at component level

In this work, we use the approach proposed by Lapa et al. [15] for calculating the reliability of a component undergoing a given maintenance policy. This model consists on a generalization of a traditional model proposed by Lewis [22] propitiating reliability calculation for any proposed schedule and not only periodical ones.

We will consider mixed systems comprised by components which alternate among on-line (on operation) and hot-standby condition and, from the failure's point of view, hot-standby components are considered operationally actives. Hence, mixed systems are considered to be integrally and permanently operating during the considered time interval (system's mission).

Consider $R(t)$ the reliability of a component which is susceptible to suffer corrective maintenance or is subjected to a preventive maintenance policy but did not already undergo any maintenance intervention at a time t, where t is the operating time or the time the component is ready to start in a hot-standby condition.

Let $T_m(i)$ be the date scheduled for the ith maintenance intervention of component m and $T_m(\mathrm{ult})$ be the date of the last maintenance intervention realized until time t. So, ult is exactly the number of maintenance interventions undergone until time t. Therefore, Eq. (1) includes such hypothesis in the traditional model:

$$R_m[t, T_m(i), T_m(\mathrm{ult})] = R[t - T_m(\mathrm{ult})] \prod_{i=1}^{\mathrm{ult}} R[T_m(i) - T_m(i-1)], \quad T_m(\mathrm{ult}) \leq t < T_{\mathrm{mis}} \quad (1)$$

As we intend to consider the influence of the maintenance suffered by one component over whole system's operation, we assume that the component is out of operation during its maintenance time period (outage time) $\Delta_m(i)$. We also consider a probability p of doing a bad (non-satisfactory) maintenance:

$$R_m[t, T_m(i), T_m(\mathrm{ult})] = \begin{cases} R[t - T_m(\mathrm{ult})](1-p)^{\mathrm{ult}} \prod_{i=1}^{\mathrm{ult}} R[T_m(i) - T_m(i-1)], & T_m(\mathrm{ult}) \leq t < T_{\mathrm{mis}} \\ 0, & T_m(i) \leq t \leq T_m(i) + \Delta_m(i) \end{cases} \quad (2)$$

Note that Eq. (2) is not exactly the component's reliability, once it is a cumulative distribution function and could not return values smaller than those already obtained. Hence, Eq. (2) represents both the reliability during the operational and the non-operational state during the outage time.

The factor p (probability of unsatisfactory maintenance) introduces a new condition, in which it is considered that a maintenance intervention may sometimes not contribute