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An integrated systemic model for optimization of condition-based maintenance with human error

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ABSTRACT

This paper proposes an integrated systemic model for the integration of human reliability model with condition based maintenance (CBM) optimization. The problem of CBM optimization is formulated as finding the optimum parameters of a function for condition monitoring (CM) scheduling so that the average unit cost (AUC) of CBM system is minimized. The concept of functional resonance is employed to analyze human-induced failure scenarios emergent from erroneous functional dependencies. To quantify human reliability in CBM, the functional characteristics of human error in CBM as well as the main performance influencing factors (PIFs) are identified. The algorithms of diagnostics and prognostics are integrated in the simulation model of CBM. Then an exact simulation-optimization algorithm based on the use of two joint Fibonacci algorithms is proposed for global optimization of CM scheduling with human error. A sensitivity analysis has been performed based on the newly developed model considering multiple levels of human errors in CBM functions to observe the effects of human errors on overall system cost. The model is also useful in demonstrating the importance and effects of improving human and organizational aspects as well as technical aspects such as the accuracy and relevance of CM technology and the accuracy of prognostics algorithm.

1. Introduction

Maintenance-related human errors have imposed heavy costs on industry. Research studies have reported on the significant role of maintenance-related human errors in aviation accidents [1–3], hazardous events in nuclear power plants [4], and software faults [5]. Dhillon and Liu [6] reported the impact of human errors in maintenance as found in the literature and come to the end with the finding that human error in maintenance is a pressing problem.

Generally, there exist two types of preventive maintenance schemes, i.e. time based maintenance (TBM) and condition-based maintenance (CBM). For CBM, the action taken after each inspection is dependent on the state of the system. It could be no action, or minimal maintenance to recover the system to the previous stage of degradation, or major maintenance to bring the system to as good as new state. For time-based preventive maintenance, the preventive maintenance is carried out at predetermined time intervals to bring the system to as good as new state.

Many researchers have reported on the superiority of condition based maintenance and predictive maintenance polices over traditional scheduled time based maintenance [7,8]. However, in reality such strategies involve human in different functions including condition monitoring, diagnostics and prognostics. Human performance is not always perfect and therefore the effectiveness of new maintenance strategies should be assessed in presence of human errors.

The main objective of this study is to integrate human reliability model into the cost optimization of CBM. Moreover, the functional and organizational aspects of human error in CBM are studied. This paper proposes a model for CM scheduling optimization in which the concept of functional resonance is used to identify and report human errors in CBM. Specifically, human errors in CM including diagnostics and prognostics are separated from human errors in maintenance work including repair, replacement, and preventive maintenance. Both human errors in CM and maintenance are quantified in terms of human error probabilities (HEPs) and are embedded in the discrete-event simulation model of CBM system. Moreover, diagnostics and prognostics (D–P) algorithms are included in the system model with the aid of Monte Carlo simulation.

The contribution and significance of this study is fourfold. First, this is the first study that investigates human error in CBM functions and develops a systemic model for integration of human error in CBM optimization. Second, With reference to the functional and contextual analysis of human error in CBM, human error probabilities in different functions of CBM system are calculated. Third, this paper proposes an exact simulation-optimization model

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to optimize CM scheduling with respect to erroneous diagnostics and prognostics. To do this, the Monte Carlo simulation models of diagnostics and prognostics are embedded in the discrete-event simulation model of CBM system. This embedding enables optimization in a more realistic decision making environment. Fourth, a design of experiment is performed and the effects on optimum system cost of three factors: (i) human error in CM, (ii) human error in maintenance, and (iii) the accuracy and relevance of condition monitoring technology, are analyzed by the use of analysis of variance (ANOVA) technique.

The remainder of the paper is organized as follows. In Section 2 the current literature on modeling human error in maintenance and CBM optimization is reported. Section 3 presents an outline of the proposed systemic model and its subsequent Sections 4 and 5 elaborate the details of the proposed model components. Section 6 illustrates the simulation-optimization procedure used to solve the problem of CBM cost optimization. Section 7 presents an experiment with the proposed model and discussion on its results. Finally paper ends with main findings and conclusions.

2. Literature review

2.1. CBM optimization

CBM optimization problem can be represented as a problem of finding some optimum decision variables for maintenance decision making based on a health criterion of the operating system. This health criterion could be the real degradation state of the system (x) or the monitored condition of the system (z). Table 1 summarizes research studies concerning CBM optimization. The main features of these studies are specified in three categories of CBM system specification, decision making, and problem solving.

In Table 1, some studies have assumed that the deteriorated state of the system can be observed directly and the maintenance decision is based on the degradation state of the system (x). Therefore, these systems do not include any diagnostics and prognostics algorithms. This simplification allows for analytical solutions [20] but it is very unrealistic as in real situations only condition monitoring variables (z) are accessible. Despite it is very interesting to have closed-form solution for the CBM system, to speed up optimization algorithms, simplified system settings may fail to have real-world applicability and usefulness.

There is an emerging trend towards uses of simulation for maintenance optimization which has changed the maintenance view [21]. When diagnostics and prognostics algorithms are to be embedded in CBM optimization model, having a closed-form solution for system cost, availability and reliability becomes more complicated and hard to obtain. Here, simulation can be a useful tool in maintenance optimization.

2.2. Maintenance modeling with human error

Worse or worst maintenance [22–25] are maintenance actions which un-deliberately make the system failure rate increase or make the system breakdown. Brown and Proschan [26] stated some types of imperfect, worse or worst maintenance due to the maintenance performer: repairing the wrong part, partial repairing, damaging adjacent parts, incorrectly assessing the condition

Table 1
Features of CBM optimization models.

Reference study	CBM system specification			Decision making			Problem Solving	
	Degradation process	Monitoring intervals	Diagnostics/ prognostics algorithm	Decision based on	Objective	Decision variable(s)	System analysis approach	Optimization algorithm
Marseguerra et al. [9]	Stochastic deterioration with both negative and positive stationary and independent changes	Continuous	–	x	Availability and net profit	Preventive degradation threshold (replacement threshold)	One unit/MC simulation	Genetic algorithm
Rosqvist [10]	General age model with known median and 95% confidence interval	Continuous	Expert judgment	z	Expected life time utility	Replacement threshold	One unit/ simulation	–
Barata et al. [11]	General; stochastic deterioration with non-negative, stationary and independent increments	Continuous	–	x	Long-run unit cost	Optimal degradation threshold of maintenance intervention	Multi component/ MC simulation	Simple search
Grall et al. [12]	General	Discrete	–	x	Long-run unit cost	Replacement and inspection threshold	One unit/ mathematical	Mathematical programming
Castanier et al. [13]	General	Discrete	–	x	Long-run unit cost	Multi level thresholds for inspection/replacement coordination	Two units/ numerical computation	Numerical
Cadini et al. [14]	Paris–Erdogan model	Discrete	Particle Filtering	z	Long-run unit cost	Replacement threshold	One unit/MC simulation	–
Curcuru et al. [15]	Markovian degradation process, first order autoregressive model with drift	Discrete	Inverse transform	z	Long-run unit cost	Replacement and inspection threshold	One unit/ Bayesian and simulation	Graphical search
Van der Weide et al. [16]	Cumulative stochastic point process with shocks	Discrete	–	x	Discounted Long-run unit cost	Critical threshold for total damage	One unit/ numerical algorithm	–
Tian et al. [17]	No specific model – Weibull for age	Discrete	ANN	z and age	Long-run unit cost	Failure probability values at the component and system levels	Two units/ simulation	–
Tian and Liao [18]	No specific model – PHM for age	Discrete	–	z and age	Long-run unit cost	Risk thresholds at the component and system levels	Multi units/ numerical	Mathematical programming
Flage et al. [19]	General	Discrete	–	x	Unit cost with safety constraints	Inspection scheduling function parameters and preventive degradation threshold	One unit/ Bayesian and simulation	Graphical search