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Safety constraints applied to an adaptive Bayesian condition-based maintenance optimization model

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Abstract

A model is described that determines an optimal inspection and maintenance scheme for a deteriorating unit with a stochastic degradation process with independent and stationary increments and for which the parameters are uncertain. This model and resulting maintenance plans offers some distinct benefits compared to prior research because the uncertainty of the degradation process is accommodated by a Bayesian approach and two new safety constraints have been applied to the problem: (1) with a given subjective probability (degree of belief), the limiting relative frequency of one or more failures during a fixed time interval is bounded; or (2) the subjective probability of one or more failures during a fixed time interval is bounded. In the model, the parameter(s) of a condition-based inspection scheduling function and a preventive replacement threshold are jointly optimized upon each replacement and inspection such as to minimize the expected long run cost per unit of time, but also considering one of the specified safety constraints. A numerical example is included to illustrate the effect of imposing each of the two different safety constraints.

Keywords

Bayesian reliability; Adaptive maintenance optimization model; Safety constraint

Figures and tables from this article:

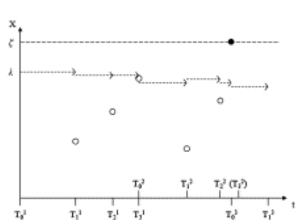

Fig. 1. Example illustration of adaptive procedure and control-limit rule: deterioration at inspections (○) and failure (•) indicated.

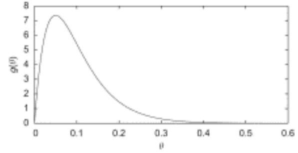

Fig. 2. Prior gamma density of θ for hyperparameter values $(\gamma,\beta)=(2,20)$.

Figure options

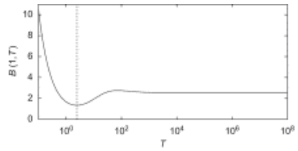

Fig. 3. $B(1,T)$ versus logarithmic T based on the prior parameter distribution; vertical line (dashed) indicates economically optimal value of T.

Figure options

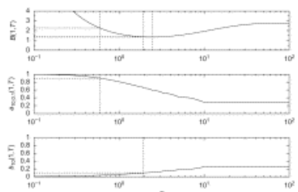

Fig. 4. $B(1,T)$, $a_{10,0.1}(1,T)$ and $b_{10}(1,T)$ based on the prior parameter distribution; vertical lines (dashed) indicate the economically optimal value of T and the optimal values of T under safety constraints 1 and 2, in this case the values of T where $a_{10,0.1}(1,T)$ drops below d_1 and $b_{10}(1,T)$ rises above d_3.

Figure options

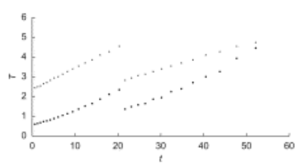

Fig. 5. Development of T_{eco} ( ) and T_{con1} (•) during simulation 1.

Figure options

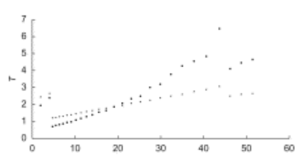

Fig. 6. Development of T_{eco} ( ) and T_{con2} (•) during simulation 2.

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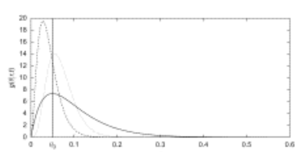

Fig. 7. Prior parameter density (solid line) and posterior parameter densities based on simulation 1 (dashed line) and simulation 2 (dotted line); vertical line (solid) indicates the true value of θ.

Figure options

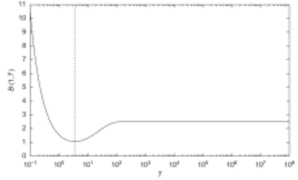

Fig. 8. $B_0(1,T)$ versus T; vertical line (dashed) indicates economically optimal value of T.

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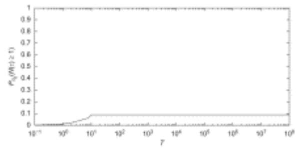

Fig. 9. $p(N(\tau)\geqslant 1|\theta_0)$ versus T.

Figure options

Table 1. Duration of and number of shocks/preventive replacements (PR)/corrective replacements (CR) during simulations 1 and 2.

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