Reliability Engineering and System Safety 154 (2016) 73–83

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

System redundancy optimization with uncertain stress-based component reliability: Minimization of regret

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ARTICLE INFO

Article history:
Received 29 January 2015
Received in revised form
20 May 2016
Accepted 24 May 2016
Available online 25 May 2016

Keywords:
System reliability
Future usage stress
Decision-making with uncertainty
Regret

ABSTRACT

System reliability design optimization models have been developed for systems exposed to changing and diverse stress and usage conditions. Uncertainty is addressed through defining a future operating environment where component stresses have shifted or changed for different future usage scenarios. Due to unplanned variations or changing environments and operating stresses, component and system reliability often cannot be predicted or estimated without uncertainty. Component reliability can vary due to a relative increase/decrease of stresses or operating conditions. The uncertain parameters of stresses have been incorporated directly into the new decision-making model. Risk analysis perspectives, including risk-neutral and risk-averse, are considered as system reliability objective functions. A regret function is defined, and minimization of the maximum regret provides an objective function based on random future usage stresses. This is an entirely new formulation of the redundancy allocation problem, but it is a relevant one for some problem domains. The redundancy allocation problem is solved to select the best design solution when there are multiple choices of components and system-level constraints. Nonlinear programming and a neighborhood search heuristic method are recommended to obtain the integer solutions for risk-based formulations.

1. Introduction

System reliability optimization problems become more realistic when considering uncertainty from associated stresses, operating conditions, etc. for different components within a system. With changing loads and stresses in the foreseeable future, a reliability model is useful to predict or determine the impact from these future usage profiles. This new model pertains to applications where it is known that stresses or operating conditions of the system will change, but it is not known the extent of the change, although possible future outcomes can be defined and enumerated.

Consider a new system design where decisions must be made regarding the components to be used, i.e., the number of redundant components and the system architecture. The Redundancy Allocation Problem (RAP) is a well-known problem solved to determine an optimal system configuration. RAP is already a difficult problem; however, now we consider that available component reliability is affected by uncertain future stresses and usage conditions. Design decisions must be made given there are multiple future usage conditions or profiles that can occur.

Aircraft launcher and recovery systems provide some of the motivation to model the anticipated future reliability of components or systems [1–3]. These systems must operate at a very high level of reliability yet it is anticipated that the airplanes using these systems will be getting heavier due to changing mission types with more required equipment, and also the distribution of airplanes using these systems will be shifting (heavier airplanes will conduct more missions). A particular aircraft launcher or recovery system is exposed to a random pattern of different airplane types, with different characteristics (weights, speeds), creating important and unique reliability issues.

RAP models are presented in this paper where opportunity loss or a regret minimization approach is proposed to directly accommodate uncertainty within the component and system reliability functions. The model formulations considering uncertainty provide additional modeling capabilities and have advantages when compared to traditional reliability models that do not account for risk and uncertainty. The model is realistic and can be applied to various industrial problems, as the uncertainty of system configurations becomes a significant issue in industry.

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http://dx.doi.org/10.1016/j.ress.2016.05.011
0951-8320/

1.1. Assumptions

- Components and systems have two states (fully functional, failed).
- Failure times of individual components are independent.
- Component failure times follow parametric Weibull distributions.
- Component failure time distributions change in response to different stress levels according to lifetime proportional models (often known as accelerated failure time models).
- Failed components do not inflict any damage on other components, and systems are non-repairable.
- All redundancy is active redundancy. Components fail at the same rate whether they are a primary or redundant component.
- Operating and usage stress profile will undergo a single shift from the current profile to a different one.

1.2. Notation

$R(\mathbf{x};t)$	system reliability as a function of design vector $\mathbf{x}$ at time t
$\mathbf{x}$	$(\boldsymbol{x}_{11}, \boldsymbol{x}_{12}, \boldsymbol{x}_{13}, \ldots, \boldsymbol{x}_{sms})$
x_{ij}	number of identical components for a particular choice jth to be used in subsystem i
s	number of subsystems in a series system
m_i	number of available component selection types or choices for subsystem i
$\mathbf{U}$	random future usage profile vector, $\mathbf{U}=(U_1, U_{2,} \ldots, U_c)$, $\mathbf{U} \in \{\mathbf{u}_1, \mathbf{u}_{2,} \ldots, \mathbf{u}_v\}$
U_k	stress factor k (a random variable)
c	number of different operating usage and stress factors
$\mathbf{u}_l$	usage profile vector for future usage l, $\mathbf{u}_l = (u_{1l}, u_{2l,} \ldots, u_{cl})$
u_{kl}	stress factor k in future usage l
p_l	probability or likelihood of future usage l, $l=1,2,.,v$
v	number of future usage scenarios
$r_{ij}(\mathbf{u}_l;t)$	reliability for jth component choice to be used in subsystem i in future usage l
$\eta_{ij}(\mathbf{u}_l)$	Weibull scale parameter of jth component choice in subsystem i for future usage l
η_{0ij}	current Weibull scale parameter for jth component choice to be used in subsystem i
β_{ij}	Weibull shape parameter of jth component choice in subsystem i
α_{ijk}	sensitivity coefficient of stress factor k for the jth component choice in subsystem i
W	weight constraint
C	cost constraint
w_{ij}	weight of jth component choice in subsystem i
c_{ij}	cost of jth component choice in subsystem i

1.3. Redundancy Allocation Problem (RAP)

This research is focused on series-parallel systems with s subsystems connected in series. Within each subsystem i, there are potentially redundant components of different choices connected in parallel as depicted by the example in Fig. 1. All redundancy is active redundancy. The numbers in the figure represent the particular component choice j. The number of identical components for a particular choice is x_{ij}, and all the components are connected in parallel within each subsystem. In the example in Fig. 1, there are $m_i=5$ functionally equivalent component choices for each subsystem, and n_i is the sum of all x_{ij} in subsystem i. For example, there are two identical components of choice 1, one component of choice 2 for subsystem 1 and three total components ($x_{11}=2$, $x_{12}=1$, $x_{13}=x_{14}=x_{15}=0$, $n_1=3$); two identical components of choice 3 for subsystem 2 ($x_{23}=2$, $x_{21}=x_{22}=x_{24}=x_{25}=0$, $n_2=2$); and for subsystem 3, $x_{31}=x_{32}=x_{33}=0$, $x_{34}=3$, $x_{35}=1$, $n_3=4$, and so on. Components for a subsystem are selected by solving the RAP subject to system-level cost and weight constraints.

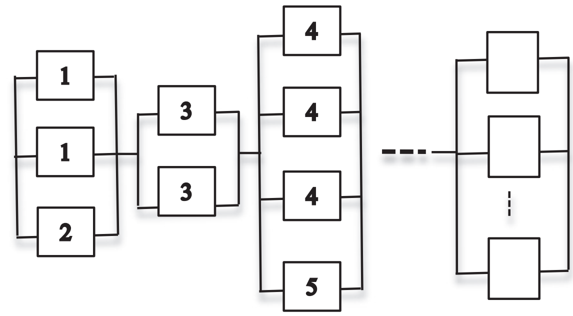

Fig. 1. Series-parallel system with multiple choices of components in each subsystem.

System reliability with deterministic component reliability and active redundancy is $R(\mathbf{x};\, t) = \prod_{i=1}^{s}\left(1 - \prod_{j=1}^{m_i}(1 - r_{ij}(t))^{x_{ij}}\right)$ where based on the Weibull distribution, $r_{ij}(t) = \exp\left(-(t/\eta_{ij})^{\beta_{ij}}\right)$. The reliability models in this paper are all for applications with active redundancy (or hot standby) and Weibull distributed component failure times (with constant stress levels). The Weibull distribution is a widely applied and flexible distribution, so this is not very restrictive. On the other hand, an important future extension to these models will be to make them more general and to apply to cold-standby redundancy and mixed redundancy types.

RAP considering uncertain conditions was studied by Hada et al. [2,3]. They evaluated the use of stress covariates for changing stress profiles for aircraft systems. Component-level methods were used to model stress functions for future reliability predictions. A general modeling approach for components with changing future stress levels was presented by Johnson et al. [1].

To compensate for uncertainty in the RAP, risk minimization can be considered when selecting a system reliability objective function. This stochastic optimization problem can be transformed to an equivalent deterministic problem by defining a future usage stress profile composed of discrete usage or stress scenarios. A risk-neutral approach is to maximize the expected value of the uncertain system reliability. However, if the consequences of low reliability are very dire or undesirable, it may be too risky to use the expected value as an objective function. Even if it is unlikely, the worst or most extreme conditions can occur sometimes, and for some applications, it is important that the system be maximally reliable even then. In these cases, it may be advantageous to use an alternative optimization strategy. The system designer can adopt a minimax regret with robust decision criteria to address uncertainty over possible usage scenarios. In this approach, a regret function is defined and the objective is to minimize the maximum regret given the uncertainty.

For RAP with uncertainty, a decision-maker needs to decide whether they are risk-neutral or risk-averse. The optimal decision is generally different for the two formulations, although for same applications they can be very similar. Given many opportunities, the risk-neutral decision-maker achieves higher system reliability more often. However, they may occasionally achieve unsatisfactorily lower reliability. The risk-averse decision-maker is concerned with the least desirable solutions even if the probability is low. The risk-averse decision-maker may have marginally lower reliability more often, but they will more rarely have very poor reliability.

For decision-making with an uncertain performance criterion, the 'regret' of a decision can be defined as the relative