Preventive maintenance scheduling and replacement using parallel evolutionary algorithms

Anthony O. Ikechukwu[1], Shawulu H. Nggada[2], and José Ghislain Quenum[1]

[1] Namibia University of Science and Technology, Windhoek, Namibia
ikechukwu_anthony@yahoo.com, jquenum@nust.na,
[2] Higher Colleges of Technologies, Ras Al Khaimah, United Arab Emirates
shnggada@gmail

Abstract. The dependability of *safety-critical systems* prescribes the replace policy when the reliability of any of its components drops below a predefined *unacceptable* level. Various techniques have been used in the past to draw up the perfect preventive maintenance schedule based on the meantime to failure (MTTF). This paper presents a review of *parallel evolutionary algorithms* to accomplish this task.

Keywords: Dependability · Maintenance Scheduling · Component replacement · Island Model · Strength Pareto Evolutionary Algorithm 2 (SPEA2) · Optimisation · Reliability and Availability · Safety Critical Systems.

1 Introduction

With modern safety-critical systems displaying multiple and complex failure modes, orthodox manual analysis of systems turn out to be more and more complicated and error-prone. Even rule-based and traditional safety and reliability analysis techniques are outdated. *Preventive maintenance* (PM), the introduction of scheduled maintenance for all or critical components of the system, is introduced to address these limitations. *Preventive maintenance* is naturally expressed as a combinatorial optimisation problem [4, 2].

Typically, an appropriate preventive maintenance schedule is meant to elongate the useful life of components [5] through repairs based on the meantime between failures (MTBF). However, at a certain point, these components will become unmaintainable. In this work, we extend the preventive maintenance with a replacement policy according to the meantime to failure (MTTF). In this paper, we present a review of parallel evolutionary algorithms for perfect preventive maintenance based on a replacement policy.

2 Parallel Evolutionary Algorithms

Evolutionary algorithms (EA) represent a family of algorithms used in artificial intelligence (AI) where the problem space is searched by focusing on the fittest

individuals over several generations. An EA starts with an initial population, which it evaluates to select the fittest. After that, the algorithm iterates through the selection of the fittest, crossover and mutation until the termination criteria (an expected fitness or the maximum number of iterations has been reached) are met.

Because EAs are generally computationally costly, previous research efforts have developed parallel versions of EAs (parallel evolutionary algorithms, PEAs), using a single population or multiple sub-populations. These parallelisation efforts prove useful while executing EAs on massively parallel computers or supercomputers. Alba [1] discusses three variants of PEAs, including a *master-slave* PEA, a *fine-grained* PEA and a *coarse-grained* PEA. A *master-slave* PEA uses a single population but distributes the crossover, mutation and fitness evaluation to other processors. A *fine-grained* PEA also uses a single population and confines individuals within a spatial structure, where they can only interact with their neighbours. Finally, a *coarse-grained* PEA or island model which divides the population into several sub-populations. The latter then have an amount of migration among them.

3 Evolutionary Selection Algorithm

3.1 The Non-dominated Sorting Genetic Algorithm II ($NSGA\ II$)

$NSGA\ II$ [3] is a multi-objective, multi-directional optimisation algorithm. It is an improved version of $NSGA$ that mitigates some its drawbacks. For example, $NSGA$ does not have an elitist feature, which improves the performance of the search process as it retains good solution from generation to generation. This limitation is addressed in $NSGA\ II$. As well, parameter tuning is handled in In $NSGA\ II$. Finally, $NSGA\ II$ is a Pareto frontier algorithm; i.e., it produces optimal solutions.

3.2 Strength Pareto Evolutionary Algorithm 2 ($SPEA$ 2)

$SPEA$ 2 [6] is an enhanced elitist multi-objective EA which uses an improved fitness allotment approach different from what is available in its predecessor $SPEA$. The fitness assignment approach integrates density information and the archive. Additionally, a clustering technique, which is introduced as soon as the non-dominated front surpasses the archive border, is substituted with another truncation method with similar characteristics and nevertheless keeps the boundary details. Furthermore, in $SPEA$ 2 the archive members are involved in the reproduction process.

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