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Preventive maintenance scheduling by variable dimension evolutionary algorithms

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Abstract

Black box optimization strategies have been proven to be useful tools for solving complex maintenance optimization problems. There has been a considerable amount of research on the right choice of optimization strategies for finding optimal preventive maintenance schedules. Much less attention is turned to the representation of the schedule to the algorithm. Either the search space is represented as a binary string leading to highly complex combinatorial problem or maintenance operations are defined by regular intervals which may restrict the search space to suboptimal solutions. An adequate representation however is vitally important for result quality.

This work presents several nonstandard input representations and compares them to the standard binary representation. An evolutionary algorithm with extensions to handle variable length genomes is used for the comparison. The results demonstrate that two new representations perform better than the binary representation scheme. A second analysis shows that the performance may be even more increased using modified genetic operators. Thus, the choice of alternative representations leads to better results in the same amount of time and without any loss of accuracy.

Keywords: Evolutionary algorithms; Maintenance scheduling; Variable length representation

1. Introduction

Scheduling the preventive maintenance of technical systems is a nontrivial optimization task which is influenced by many different aspects like reliability and cost optimization. Normally, these two aspects are conflicting as short maintenance intervals cause high maintenance costs. Depending on the system simulation, the resulting optimization problems may be highly nonlinear, complex and intractable for analytical solutions. If Monte Carlo techniques are used, then stochasticity is added and the problems become even more difficult to tackle. In such cases, the use of black box global optimization strategies such as simulated annealing and evolutionary algorithms may increase the result quality.

The optimization of a preventive maintenance schedule can be viewed as a three layered setup (Fig. 1). The *system model* simulates the technical system over a fixed time period, including maintenance events and may be of deterministic or stochastic nature. It receives a maintenance schedule containing a list of preventive maintenance events for all components. Its output are values such as the reliability over time $R(t)$ and the maintenance costs CS.

The topmost layer is the *optimization strategy*. Black box optimization strategies are problem solving heuristics which 'intelligently guess' new solutions based on older experiences and some general assumptions. There is no necessity to know more about the function to optimize than its output values and the dimension and constraints on the decision values (input variables). Perhaps, the most popular global optimization strategies belong to the field of evolutionary algorithms [1,2] while other strategies such as dynamic programming [3] and tabu search [4] have also been used. In case of stochastic objective functions [5,6] propose the use of noisy Evolutionary Algorithm approaches which model the stochastic nature of the algorithms and thus are preferable to deterministic methods using iterative sampling for noise elimination. All of this methods share one commonality: they are vector-based, the decision values are restricted to vectors with binary/integer/real elements of constant length, so called decision vectors $\mathbf{x}$. We will show that this is both a nonintuitive way of schedule representation and may lead to suboptimal results.

The middle layer, which we denote as *input/output coding* (I/O coding) is rarely investigated by researchers but simply stated. The output coding maps the system model output to an

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Nomenclature

$R(t)$	system reliability function
CS	maintenance cost
C_i	component i
$\|C\|$	number of components
α,β	Weibull parameters
$\mathrm{PF}_i(a_i)$	failure probability of C_i with age a_i
$\mathbf{x}$	decision vector $\mathbf{x}$
x	decision vector array
X	decision space
$\mathbf{x}_{\min},\mathbf{x}_{\max}$	borders of the decision space
$\mathbf{y}\in Y$	objective vector $\mathbf{y}$, decision space Y
w_1,w_2	weight factors
M	maintenance matrix
T	number of simulation points of time
$d_{\min},d_{\max}$	minimal and maximal dimension of the decision space X
dim_a	vector array dimension
$\mathrm{dim}(\mathbf{x})$	dimension of vector $\mathbf{x}$
p_{cross}	crossover probability
p_{mut}	point mutation probability
BIN	BINary coding
BINC	BINary component coding
VA	variable length absolute coding
VAC	variable length absolute component coding
VR	variable length relative coding
VAC	variable length relative component coding
LIC	length independent crossover
LDC	length dependent crossover

objective vector. This vector could be of one dimension (single objective optimization) or of more than one dimension (multi-objective optimization). The input coding is responsible for the transformation of the decision vector to a maintenance schedule. The algorithm performance may react very sensible on the choice of the input coding, and thus the investigation of various input codings may greatly enhance the optimization results.

In this work, we compare different input coding functions and line out the influence of these functions on the optimization results. Section 2 introduces the system model and output coding used. Section 3 introduces the six different input codings investigated. In Section 4 the optimization strategy, an evolutionary algorithm is presented and some extensions to cope with variable dimension decision values are shown. Section 5 shows the results of some comparative tests evaluating the proposed input codings and algorithm extensions. Finally, Section 6 draws conclusions of this work and proposes some further research directions.

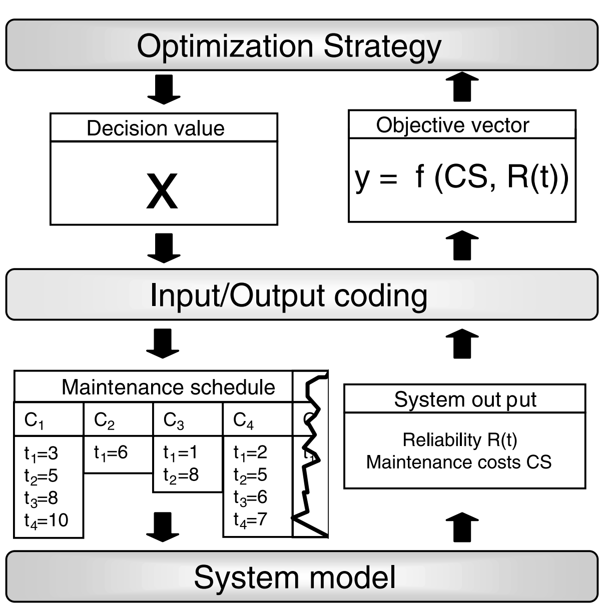

Fig. 1. Maintenance optimization process as a three layered model.

2. System model and output coding

As a black box test case, we used a simplified system with ten components $C_{i=1\ldots n}$ represented as a reliability block diagram (Fig. 2). Failure distribution of the components i were defined as Weibull distributions with characteristic life α_i and shape β_i, depending

$$\text{Weibull}: \mathrm{PF}_i(a_i) = 1 - \mathrm{e}^{-(a_i^{\beta}/\alpha)} \quad (1)$$

Maintenance durations are assumed as very short and therefore not affecting the working state of the component. If a component fails, the failure remains undetected (hidden) and it is only replaced in a preventive maintenance action. Corrective maintenance is not considered. After the replacement, the component is in an as-good-as-new state. All hidden failures are removed. Simulation outputs are the reliability function $R(t)$ which describes the system reliability as a function of simulation time and the maintenance costs CS of the maintenance schedule. In this simple model, we assume that each maintenance event has the same costs and no other costs are accrued. The system was simulated for 5 years with a simulation step size of 30 days leading to $T=60$ simulation steps. Each step is a possible point of time for maintenance.

$R(t)$ was multiplied with an importance index $I(t)$ that reflects the costs of a failure depending on the simulation time. The cost of a system failure may vary in reality due to several reasons, e.g. contractual terms, the amount of customers and spare situation. If this is the case, periodic maintenance schedules will not lead to the optimal solution, and codings allowing nonperiodic schedules are necessary. We assumed high failure costs in winter months and low costs in summer months. This is realistic for gas networks or power plants where load increases in colder seasons.