Model to study the effect of workforce in a safety equipment and its optimization

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Abstract

Many industrial sectors are concerned on developing optimal maintenance planning because of the importance of maintenance on the economy and safety. Traditionally, the maintenance planning is formulated in terms of a multi-objective optimization problem where reliability, availability, maintainability and cost act as decision criteria and surveillance test and maintenance strategies act as decision variables. However, the appropriate development of each maintenance strategy depends not only on the maintenance intervals but also on the resources available to implement such strategies. To solve the multi-objective optimization problem Particle Swarm Optimization (PSO) can be used. PSO is a stochastic global optimization technique inspired by social behavior of bird flocking or fish schooling. In this paper the multi-objective optimization of the maintenance of a nuclear power plant safety equipment using PSO is presented.

Keywords: Reliability,Maintainability, Availability, Particle Swarm Optimization

1. Introduction

Traditionally, maintenance planning in complex systems such as Nuclear Power Plants (NPPs) is focused on achieving high levels of reliability, availability, maintainability and a minimum cost. To find the best planning usually, only surveillance tests and maintenance task intervals are taken into consideration. Many studies have been developed in this period aimed at improving safety systems, with the main focus on developing designs that use more reliable and redundant equipment (e.g. intrinsic reliability allocation) and implementing an appropriate surveillance and maintenance policy to assure that an acceptable

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standard of reliability, availability and maintainability (RAM) of the safety systems is kept during all the plant operational life (e.g. testing and preventive maintenance optimization) [1, 2, 3, 4, 5]. However the appropriate development of each maintenance strategy depends not only on the maintenance intervals but also on the human resources available.Recent studies concluded that the implementation of a given maintenance plan adopting adequate test surveillance and maintenance frequencies together with and workforce can suppose large deviations from the RAM and cost goals obtained when only surveillance test and maintenance frequencies are considered [6]. Therefore, the consideration of workforce to perform a surveillance test or maintenance activity becomes an important variable to design an optimum maintenance plan. In other fields, as in manufacturing systems, the effect of workforce is taken into consideration to obtain an optimal production plan [7]. This paper proposes an approach to include the effect of the number of workers and their skills to perform maintenance in unavailability and cost analytical models. Thus in section 2 the extended models are presented. Section 3 is devoted to the problem formulation and section 4 briefly describes the fundamentals of Particle Swarm Optimization. In section 5 a case of application focused on the maintenance plan optimization of a set of motor-driven pumps is presented. Finally, section 6 presents the main conclusions obtained from this application.

2. Unavailability and Cost models

The total unavailability of a safety equipment is obtained by quantifying the following contributions [1]:

$$u_r = \left(1 - \frac{1}{\lambda I}\left(1 - e^{-\lambda I}\right)\right) \approx \rho + \frac{1}{2}\lambda I \ , \tag{1}$$

$$u_s = f_s d_s \ , \tag{2}$$

$$u_n = f_n d_n \ , \tag{3}$$

where Eqn. (1) represents the unavailability associated with an undetected failure corresponding to the particular sort of failure cause being considered, I is the interval to perform a scheduled maintenance task that is intended or supposed to detect the occurrence of such failure, ρ represents a cyclic or per-demand failure probability and λ is the standby failure rate. Eqn. (2) represents the unavailability contribution associated with a scheduled testing or maintenance task, where f_s is the scheduled activity frequency, given by $f_s = 1/I$, and d_s is the duration of such activity. Eqn. (3) represents the unavailability contribution associated with a non-planned maintenance task, where f_n and d_n represent the frequency and downtime of the activity, respectively. Regarding the cost, the yearly cost contribution of performing planned testing or maintenance, and non-planned maintenance can be evaluated as [1]:

$$c_s = 8760\, f_s\, c_{1s} \ , \tag{4}$$

$$c_n = 8760\, f_n\, c_{1n} \ , \tag{5}$$

where c_{1s} and c_{1n} represent the unitary cost as a consequence of performing one single task, scheduled or non-planed, respectively, which can be formulated using the following relationship:

$$c_{1i} = N_P c_{HP} T_P + N_E c_{HE} T_E \ , \tag{6}$$

where T_P and T_E, represent the time spent by the N_P own and N_E external personnel, respectively. In addition, c_{HE} is the hourly cost for external personnel and c_{HP} is the hourly cost for own personnel.

To consider the effect of human resources in the analytical models, it is necessary to extend the existing models to include the workforce [1], i.e. the number of workers involved in a maintenance task and theirs skills to perform such maintenance [7] influences the unavailability and cost criteria. Thus, more skilled workers will result in less time to perform an activity and this will influence the equipment unavailability level. On the other hand, as more workers are assigned to perform a maintenance task, its duration will decrease until a certain value, what improves the equipment unavailability but increases the cost. So, the effect of the workforce assigned to perform a surveillance or maintenance task results in a different duration of the activity depending on the human resources available. In a similar way, as it is done in production systems to quantify this effect, the real duration of the activity, d, i.e. d_s and d_n in equations (2) and (3), can be calculated using the following expression:

$$d = d' \left(c + (1 - c) \left(\eta_P N_P + \eta_E N_E\right)^{r_a}\right) \ , \tag{7}$$

where d', is the scheduled time to perform an activity, c is the percentage of the scheduled time that cannot be reduced regardless the number of workforce assigned to that activity, N_P and N_E are the number of own and external personnel involved in a task, respectively. And η_P and η_E, represent the efficiency of own personnel and external workforce to perform a task. Finally, r_a in Eqn. (7) represents the reduction in time due to the total amount of workforce involved in such activity. which can be evaluated, based on the expression proposed in [7], as :

$$r_a = \frac{\log_{10}\left(\frac{r_P N_p + r_E N_e}{N_p + N_e}\right)}{\log_{10} 2} \ , \tag{8}$$

Where r_P and r_E, are similar to the learning rate introduced in [7], but in this case they depend on the number of workers involved in the activity. In Fig. 1, the reduction in time depending on the human resources assigned to perform such activity is shown. It can be observed that the downtime cannot be reduced below a certain value (20 hrs. in the example). Additionally, Fig. 1 shows that the reduction is faster if the workforce assigned to perform this work corresponds to external personnel since they are more skilled to perform such work.

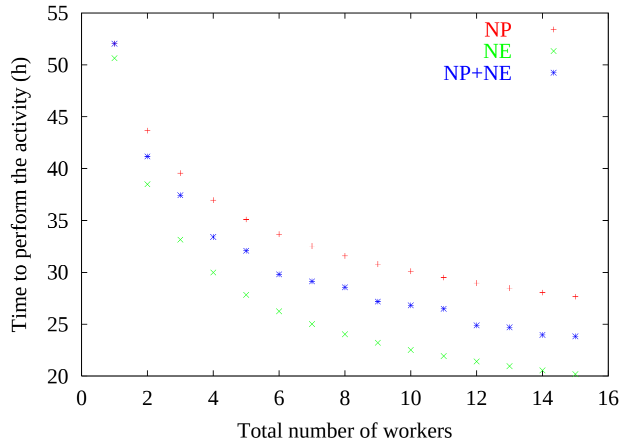

Figure 1: Time reduction vs workforce.

3. Problem formulation

The extended models can be used as objective functions in a multi-objective optimization process to obtain a set of solutions corresponding to optimum maintenance plan. This work, transforms the multi-objective into a Single-objective optimization problem (SOP) using the concept of effectiveness:

$$y = f(\mathbf{x}) = 1 - \left(\omega e_u(\mathbf{x}) + (1-\omega)\, e_c(\mathbf{x})\right) \ , \tag{9}$$

where $e_u(\mathbf{x})$ and $e_c(\mathbf{x})$ are the unavailability and cost effectiveness, defined as:

$$e_u(\mathbf{x}) = \frac{U_r - U}{U_r - U_m} \ , \quad e_c(\mathbf{x}) = \frac{C_r - C}{C_r - C_m} \ , \tag{10}$$

where U_r represents the equipment unavailability for the initial maintenance plan, and C_r is the associated cost. And U_m and C_m are the optima values obtained from solving to SOPs corresponding to the unavailability and cost optimization, respectively. ω, in Eqn. (9) is the weighting coefficient that range in the interval $[0, 1]$.

4. Particle Swarm Optimization

The Particle Swarm Optimization (PSO) method is a member of the wide category of Swarm Intelligence methods [8]. It was originally proposed by J. Kennedy as a simulation of social behavior, and it was initially introduced as an optimization method in 1995 [9]. PSO is related with Artificial Life, and specifically to swarming theories. This optimization technique has been proved to obtain good results in constrained optimization problems [10].

PSO is similar to Evolutionary Computation techniques in that, a population of potential solutions to the problem under consideration, is used to probe the search space. However, in PSO, each individual of the population has an adaptable velocity (position change), according to which it moves in the search space. Moreover, each individual has a memory, remembering the best position of the search space it has ever visited. Thus, its movement is an aggregated acceleration towards its best previously visited position and towards the best individual of a topological neighborhood. Since the acceleration term was mainly used for particle systems in Particle Physics, the pioneers of this technique decided to use the term particle for each individual, and the name swarm for the population, thus, coming up with the name Particle Swarm for their algorithm [9].

Assuming that the search space is D-dimensional, the $i-th$ particle of the swarm is represented by the D-dimensional vector $\mathbf{X_i} = (x_{i1}, x_{i2}, ..., x_{iD})$ and the best particle in the swarm, i.e. the particle with the smallest function value, is denoted by the index g. The best previous position (i.e. the position giving the best function value) of the $i-th$ particle is recorded and represented as $\mathbf{P_i} = (p_{i1}, p_{i2}, ..., p_{iD})$, while the position change (velocity) of the $i-th$ particle is represented as $\mathbf{V_i} = (v_{i1}, v_{i2}, ..., v_{iD})$. Following this notation, the particles are manipulated according to the following equations:

$$v_{id} = w\ v_{id} + c_1 r_1 \left(p_{id} - x_{id}\right) + c_2 r_2 \left(p_{gd} - x_{id}\right) \tag{11}$$

$$x_{id} = x_{id} + \xi v_{id}\ , \tag{12}$$

where $d = 1, 2, \ldots, D$; $i = 1, 2, \ldots, N$, and N is the size of the swarm, w is called inertia weight; c_1, c_2 are two positive constants, called cognitive and social parameter respectively; r_1, r_2 are random numbers, uniformly distributed in $[0, 1]$ and ξ is a constriction factor, which is used, alternatively to w to limit velocity.

The inertia weight, w, is employed to control the impact of the previous history of velocities on the current one. This parameter regulates the trade-off between the global and local exploration abilities of the swarm. A large inertia weight facilitates global exploration, while a small one tends to facilitate local exploration. A suitable value for the inertia weight w usually provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate the optimum solution. Initially, the inertia weight was constant. However, experimental results indicated that it is better to initially set the inertia to a large value, in order to promote global exploration of the search space, and gradually decrease it to get more refined solutions [10]. Thus, an initial value about 1.2 and a gradual decline towards 0 can be considered as a good choice for w.

The parameters c_1 and c_2, in Eqn. (11), are not critical for PSOs convergence. However, proper fine-tuning may result in faster convergence and alleviation of local minima. Experimental results indicate that $c_1 = c_2 = 0.5$ might provide even better results.

Table 1: Motor-driven pump dominant failure causes.

Cause	Code	Description
$fc1$	IAL	Inadequate lubrication
$fc2$	DEM	Damaged electric or electronic module
$fc3$	MBW	Motor bearing wear
$fc4$	PIW	Pump impeller wear
$fc5$	SPD	Set point drift
$fc6$	MIS	Misalignment

Table 2: Maintenance plan selected to cover dominant failures causes.

Task	I (hrs)	Failure causes					
		$fc1$	$fc2$	$fc3$	$fc4$	$fc5$	$fc6$
Lub oil change (t1)	26000	Yes	No	Yes	No	No	No
Operational test (t2)	13000	Yes	No	No	No	Yes	No
Visual inspection Motor (t3)	26000	Yes	Yes	No	No	No	No
Visual inspection Pump (t4)	26000	No	No	No	Yes	No	Yes

5. Case of application

The case of application is focused on optimizing the maintenance plan of a set of motor-driven pumps, which is a Nuclear Power Plant safety equipment, considering as decision criteria the equipment unavailability and cost and as decision variables the maintenance and test frequency, the number of own personnel and external workforce.

Table 1, shows the six dominant failure causes considered for the motor-driven pump analyzed. In addition, Table 2, shows the maintenance plan selected in [11], which allows covering all the dominant failure causes of the equipment, and the maintenance intervals, I, actually implemented in plant. Each couple failure cause and task introduces a contribution to the equipment unavailability and cost. These contributions are quantified using the models introduced in section 2. The total unavailability and cost are computed by the aggregation of all contributions.

Table 3, shows the data related to human resources, needed to quantify the cost using the Eqn.(6), Eqn.(7) and Eqn.(8). Data related to the equipment reliability characteristic and others not included herein are the same as proposed in Ref. [12].

The optimization has been performed using a Particle Swarm Algorithm, implemented in MatLab [13], using Eqn. (9) as objective function, and the equations presented in section 2 to quantify the unavailability and cost criteria. The decision variables considered are the maintenance intervals of the four tasks identified in table 2 to cope with all the dominant failure causes and the number

Table 3: Data related to human resources.

Parameter	Own Personnel	External Personnel
Efficency	0.9	1
Delay for unscheduled tasks	0 hrs.	3 hrs.
Delay for scheduled tasks	0 hrs.	0 hrs.
Cost	2000 euros/year	30 euros/hour
N_{eq}	100	$-$
Efficency	0.9	1
Persons (N)	$[0-10]$	$[0-10]$

Table 4: PSO parameters.

Parameter	Value
c_1	0.5
c_2	0.5
w	$1.2-0.8$
Swarm Size	25
Number of iterations	100
Number of runs	20

of own and external personnel. The values selected for the PSO parameters, which have been obtained after running the algorithm for a number of trials, are shown in Table 4.

Figure 2 shows a set of non dominated solutions considering in the optimization process the maintenance and test intervals compared with the result obtained when workforce is considered as a variable. In this Figure, it can be observed that the optimization result is quite different in the two cases analyzed and that inclusion of workforce provides better solutions for the region of the Pareto Front where unavailability and cost have similar importance in the objective function. In order to study the effect of each decision variable the partial correlation coefficients have been calculated. From this analysis it can be concluded that the interval maintenance tasks t1 and t2 are the decision variables with a greater influence on unavailability with a correlation coefficient of 0.976 and 0.982, respectively. The other decision variables present a correlation coefficients lower than 0.310. Thus, for example the correlation coefficient corresponding to external personnel has a value of -0.304. Regarding the cost, the number of the external personnel is the most influencing variable, with a correlation coefficient of 0.956, followed by the number of own personnel with a correlation coefficient of 0.738. In this case the maintenance intervals present correlation coefficients lower than 0.450 and negative.

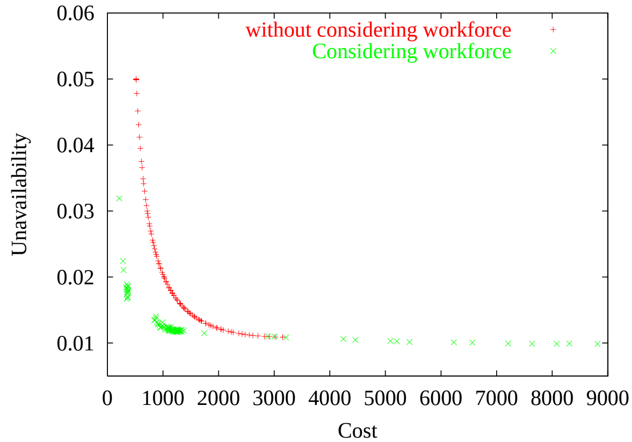

Figure 2: Comparison of non dominated solutions.

6. Conclusions

An adequate maintenance plan depends not only on the maintenance and test intervals, but also on the human resources available to perform such maintenance. The analytical models developed have been extended to take into consideration this effect. Particle Swarm has succeeded in finding an adequate set of non-dominated solutions of the maintenance optimization, and the comparison of the results obtained in the optimization process considering workforce with the results obtained by simply considering the surveillance test and maintenance frequencies, show the importance of including human resources as a variable in the optimization procedure.

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