A PSO APPROACH FOR PREVENTIVE MAINTENANCE SCHEDULING OPTIMIZATION

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ABSTRACT

This work presents a Particle Swarm Optimization (PSO) approach for preventive maintenance policy optimization, focused in reliability and cost. The probabilistic model for reliability and cost evaluation is developed in such a way that flexible intervals between maintenance are allowed. As PSO is skilled for real-coded continuous spaces, a non-conventional codification has been developed in order to allow PSO to solve scheduling problems (which is discrete) with variable number of maintenance interventions. In order to evaluate the proposed methodology, the High Pressure Injection System (HPIS) of a typical 4-loop PWR has been considered. Results demonstrate ability in finding optimal solutions, for which expert knowledge had to be automatically discovered by PSO.

1. INTRODUCTION

Particle Swarm Optimization (PSO) [1] is a population-based metaheuristic (PBM), in which solution candidates are enhanced through the simulation of a simplified social adaptation model. Several successful applications of PSO to nuclear problems are reported in literature [2, 3, 4 and 5], in which PSO demonstrated to have advantages over other well-established PBM.

In this work, a PSO for preventive maintenance scheduling optimization focused in reliability and cost is developed. The probabilistic model for reliability and cost evaluation allows the use of flexible intervals between maintenance interventions, instead of considering fixed periods. The approach propitiates a better fitting of the schedules to components' characteristics. On the other hand, due to such flexibility, preventive maintenance planning becomes a harder task. In order to deal with such complexity, genetic algorithms (GAs) [6] have been successfully applied [7 and 8]. Motivated by the fact that PSO has been demonstrating to be very competitive with other PBM (including GA), this work investigates the use of PSO as an alternative tool for preventive maintenance policy optimization with flexible interval between interventions.

Considering that PSO works in continuous space, with fixed length real-coded vectors (to encode solution candidates) and the proposed problem is discrete and may allow variable number of maintenance interventions for each system component, non-trivial encoding of solution candidates has been developed in this work.

Proposed PSO is intended to search for the optimum maintenance policy considering several relevant features such as: i) the probability of needing a repair (corrective maintenance), ii) the cost of such repair, iii) typical outage times, iv) preventive maintenance costs, v) the impact of the maintenance in the systems reliability as a whole and vi) probability of imperfect maintenance.

In order to evaluate the proposed methodology, the High Pressure Injection System (HPIS) of a typical 4-loop PWR has been considered. Preliminary results demonstrate that PSO is quite efficient in finding optimum preventive maintenance policies for the HPIS.

2. PROPOSED METHODOLOGY

2.1. Particle Swarm Optimization

PSO is Population Based Metaheuristic (PBM) inspired by the behavior of biological swarms and social adaptation. In PSO, a swarm of structures encoding solution candidates ("particles") "fly" in the n-dimensional search space of the optimization problem looking for optima or near-optima regions. The *position* of a particle represents a solution candidate itself, while the *velocity* attribute, provides information about direction and changing rate. Particles are guided by two components: i) cognitive information based on particles' own experience and ii) social information based on observation of neighbors. Let $\vec{X}_i(t) = \{x_{i,1}(t),...,x_{i,n}(t)\}$ and $\vec{V}_i(t) = \{v_{i,1}(t),...,v_{i,n}(t)\}$ be, respectively, the position and the velocity of particle i in time t, in an n-dimensional search space. Considering that $\overrightarrow{pBest}_i(t) = \{pBest_{i,1}(t),..., pBest_{i,n}(t)\}$ is the best position already found by particle i until time t and $\overrightarrow{gBest}_i(t) = \{gBest_{i,1}(t),...,gBest_{i,n}(t)\}$ is the best position already found by a neighbor until t, the PSO updating rules for velocity and position are given by:

$$v_{i,n}(t+1) = w.v_{i,n}(t) + c_1.r_1.(pBest_{i,n}(t) - x_{i,n}(t)) + c_2.r_2.(gBest_{i,n}(t) - x_{i,n}(t)) \tag{1}$$

$$x_{i,n}(t+1) = x_{i,n}(t) + v_{i,n}(t+1) \tag{2}$$

Where r_1 and r_2 are random numbers between 0 and 1. Coefficients c_1 and c_2 are given acceleration constants towards $\overrightarrow{pBest}$ and $\overrightarrow{gBest}$ respectively and w is the inertia weight.

The inertia weight, w, is the responsible for the scope of the exploration of the search space. High values of w promote global exploration and exploitation, while low values, lead to local search. A common approach to provide balance between global and local search is to linearly decrease w during the search process.

The swarm is randomly initialized. Then, while stopping criterion is not reached, particles move according velocity and positions equations (eqs. 1 and 2). The PSO algorithm pseudo code can be seen in Figure 1.

```
Algorithm PSO
begin
    for i=1 to n_particles do begin
      randomize(X_i); randomize(V_i);
    end;
    for iter=1 to iter_max do begin
       for i=1 to n_particles do evaluate (X_i);
       for i=1 to n_particles do update(pBest_i,gBest);
       for i=1 to n_particles do begin
          V_i = w*V_i+c_1*r1*(pBest_i-X_i)+c_2*r2*(gBest-X_i);
          X_i = X_i+V_i;
       end;
    end;
end.
```

Figure 1. Standard PSO pseudo code.

2.2. Optimization Problem Modeling

A typical PWR High Pressure Injection System (HPIS) once used by Lapa [7] has been considered. The HPIS can be represented by seven main components: three pumps and four valves as shown in Figure 2. In normal operation its function is to complete the inventory of the primary loop through the reactor coolant system, as well as to guarantee the seal of the pumps of this system. Under accident situations, in which the steam generators are unavailable or there is a rupture in the primary system, the HPIS is used for removing the decay heat. Considering that the reactor in operating with power above 60% and at least 2 of the 3 pumps must be available during the mission time, the top event is the unavailability to supply the inventory by both feeders.
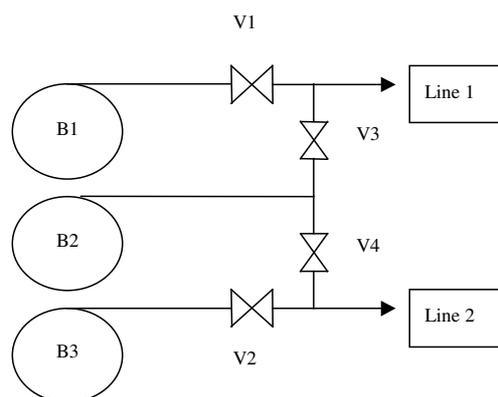
Figure 2. High Pressure Injection System

In this optimization problem, optimum maintenance scheduling for components B1, B2, B3, V1, V2, V3 must be found. Therefore, solution candidates must encode all possible scheduling combinations for all components.

Considering that PSO works with real-coded fixed length vectors, it's application to a discrete problem, in which solutions may have variable length (components variable number of maintenance interventions) is not straightforward. Firstly, a maximum of 23 interventions for each component has been established. So, a solution candidate may comprise at most 161 (23 maintenance x 7 components). Hence, it should be used a vector of 161 elements. Then, PSO position vector is given by $\overrightarrow{X}_i(t) = \{x_{i,1}(t),...,x_{i,161}(t)\}$. Figure 3 illustrate $\overrightarrow{X}_i(t)$ which present 23 elements for each component.

V_1			V_2		...		B_3		
X_0	...	X_{22}	X_{23}	...	X_{45}	...	X_{138}	...	X_{160}

Figure 3. Vector $\overrightarrow{X}_i(t)$

Note that, to allow variable scheduling length (components may have less than 23 interventions), decoding $\overrightarrow{X}_i(t)$ is not straightforward.

Considering a total operation period of 540 days and a time step of 1 day, the following steps are required to decode $\overrightarrow{X}_i(t)$ into valid scheduling.

i) $\overrightarrow{X}_i(t)$ elements are real numbers ranging from –540 to 540;
ii)   each element is rounded to the closes integer;
iii)   values from 1 to 540 represents valid days for maintenance interventions;
iv)   non-positive values mean no intervention;
v)   duplicate values are removed;

Figure 4 exemplifies such decoding procedure.

Vector X:

													V1										...	B3
x0	x1	X2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	x17	x18	x19	x20	x21	x22	...	...
32.1	-18	95.7	200	-30	-9.1	-123	301	260	-11	-521	123	498	-23	-91	-510	15.9	350	200	-10	-89	380	10	...	...

Valid days for maintenance

												V1										...	B3
32	-	96	200	-	-	-	301	260	-	-	123	498	-	-	-	16	350	200.	-	-	380	10	...	B3

Maintenance scheduling without repetitions

											V1											...	B3
10	16	32	96	123	200	260	301	350	380	498	-	-	-	-	-	-	-	-	-	-	-	...	...

Figure 4. Decoding $\overrightarrow{X}_i(t)$ into a valid scheduling.

The same objective function used by Lapa [7] has been used. Equation 3 shows such function, which should be minimized.

$$F = W_d.U + W_c.C \qquad (3)$$

Where U is the average unavailability and C the total cost for a given scheduling, calculated according to [7]. W_d vary between 0 and 1 and W_c ranges between 0 and 1/(N_COMP * MAX_INT), where N_COMP is the number of components and MAX_INT is the maximum number of maintenance interventions.

3. COMPUTATIONAL EXPERIMENTS AND RESULTS

Two case studies have been carried out. The first one is a hypothetical situation used as benchmark, in which global optimum is well known. The second one is a harder situation closer to a real problem.

3.1. First case study

To test efficiency and consistency of proposed methodology, an investigation considering the following characteristics have been done:

i)   component is not under aging (consider K_3=1 in Lapa's probabilistic model [7]) and so, maintenance does not improve reliability;
ii)   all maintenance is perfect (consider p=0 in Lapa's probabilistic model [7])

Expected optimum scheduling is "no maintenance interventions to the whole system".

Tem experiments have been made with different random seeds and typical values for C1 and C2 (both set to 2.0). Inertia weight, w, decreased from 0.8 to 0.2 in 2000 generations.

In all cases "no maintenance" have been proposed, demonstrating efficiency and consistency of the proposed approach.

3.2. Second case study

In this scenario, more realistic values for failure rates, costs for maintenance and repair, etc, has been used according to Harunuzzaman [9].

Tem experiments have been made with different random seeds and typical values for C1 and C2 (both set to 2.0). Inertia weight, w, decreased from 0.8 to 0.2 in 1000 generations.

Table 1 and 2 show obtained results.

Exp.	Particles	Seed	Cost	Unavailability	Fitness
1	20	123456789	0.0056313	0.00448557	0.0101169
2	20	7622	0.00576458	0.00423274	0.00999732
3	20	777	0.00571318	0.00429454	0.0100077
4	20	13	0.00570311	0.00437837	0.0100815
5	20	13987	0.00583616	0.00408374	0.0099199
6	50	123456789	0.00576754	0.00423455	0.0100021
7	50	7622	0.00570256	0.00430842	0.010011
8	50	777	0.00584039	0.00400797	0.00984836
9	50	13	0.00570006	0.00432445	0.0100245
10	50	13987	0.00562846	0.00455739	0.0101859

Table 1. Results for the second case study

Fitness = 0.00984836		
Valve 1	4 interventions	72-146-228-326
Valve 2	4 interventions	73-148-226-331
Valve 3	3 interventions	108-218-343
Valve 4	3 interventions	107-216-342
Pump 1	1 interventions	228
Pump 2	2 interventions	132-281
Pump 3	1 interventions	226

Table 2. Best solution found for second case study

In Table 1 it can be observed the consistency of the method in finding solutions very close to each other.

Table shows a very important feature: the knowledge discovery developed by the proposed approach. Note that Valve 1 and Pump 1 which are inline to each other stop at coincident time (t=228). Such fact improves availability. The same occurs with Valve 2 and Pump 3. Also, pumps undergo fewer interventions due to the higher cost and outage time for maintenance.

4. CONCLUSIONS

This work demonstrates the feasibility of using PSO for preventive maintenance optimization. Proposed PSO non-conventional solution candidate, encoded into fixed length real-coded vector demonstrates to be efficient to deal with a 1-day step scheduling optimization with variable number of interventions.

The efficiency and consistency of the proposed PSO approach is observed, not only on fitness values, but principally in the knowledge discovery, which allows a gain in the availability when components stop at coincident time.

Future research should be the investigation of multi-objective PSO models.

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