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Simulation of virtual radiation detectors in nuclear power plants to support equipment ageing studies based on Particle Swarm Optimization

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1. Introduction

When Nuclear Power Plant (NPP) is reaching the end of its lifetime, an environmental licensing plan with the objective of prolonging the useful life of its operation is required. A requirement for the licensing is an ageing study of electrical and electronic equipment's inside the containment building of the plant. The main ageing affects are changes in physical properties due the temperature, radiation, humidity, etc. received by the equipment since its operation starts [1]. Once the NPP doesn't have these data the ageing studies will be harmed.

In this article is proposed a methodology based on particle swarm optimization [2] in order to simulate virtual radiation detectors, using as parameters measurements of real plant detectors in order to support ageing studies [3]. For the implementation of the proposed methodology was used data from a pressurized water reactor (PWR) NPP.

The results with the proposed methodology show a promising path for solving this type of problem.

2. Methodology

PSO (*Particle Swarm Optimization*) [2][3][4] is a random search algorithm, inspired by de movement of flock of birds and school of fishes in search of food. The algorithm works simulating the movement of particles with a vector for positions and a vector for speeds. Speed vector is characterized by the balance between local search (best position visited by a single particle – *pbest*) and global search (best position visited by the group – *gbest*).

Each particle's performance is evaluated every generation by a *fitness* function, which evaluate how good the position is in relation to the solution of the problem. Every iteration the algorithm update the positions and speeds of each particle with 3 parameters:

- *w* (inertia factor) – trend of the particle keep its move in the same direction it's already moving;
- *pbest* (best individual position) – trend of the particle of moving in the direction of its best individual position;
- *gbest* (best global position) – trend of the particle of moving in the direction of group's best position;

The speed and position updates are governed by the following equations,

$$V_i(k+1) = wX_i(k) + R_1C_1\big(P_i(k) - X_i(k)\big) + R_2C_2\big(PG(k) - X_i(k)\big) \quad (1)$$

$$X_i(k+1) = X_i(k) + V_i(k+1) \quad (2)$$

with,

- R_1 e R_2 are random variables between 0 and 1;
- C_1 e C_2 are constants;
- P_i (k) is the best position value particle *i* has already visited (*pbest*);
- PG(k) is the best global position (*gbest*).

The PSO was modeled using data of the 20 detectors in different position inside the containment building of a PWR NPP in different years. Among the 20 detectors installed, the 10 most accurate where chosen in order to proceed with the study.

It was used Python Language [5] to program the algorithm with de following mathematical modeling,

$$M_{y,i} = \alpha_i . RE00_y \quad (3)$$

With:

- $M_{y,i}$ – Measurement of detector in position *i* for year *y;*
- α_i – Model constant training, goal of PSO algorithm.
- $RE00_y$ – Annual average of sensor RE00 for year *y*.

Random factors cause the algorithm do not get stuck in local solution, once it is desired a solution optimized in all the search space.

With the 10 real measurement in hand, it was created the position and the speed vectors, each with 10 elements, representing the 10 particles. With PSO it is desired find values for α_i which causes *fitness* function to be the lesser possible. *Fitness* function model is,

$$Fitness = \sqrt{\sum_{i=1}^{10}(\alpha_i . RE00_y - M_{y,i})^2} \quad (4)$$

3. Results and Discussion

With the problem modeled, several tests with different constants for PSO were made. The tests were evaluated and the constants for the best result are presented in Table I, and the results are shown in Table II.

Table I: Constants used in PSO.

Constants	Values
w	0.6
C_1	1.8
C_2	1.8

Table II: PSO's results for the problem proposed.

Detector	Alpha correlation	Year 1	Year 2
7	0.0164762548	**1.741045844**	**1.835454783**
8	0.0094907093	*1.002883248*	*1.057265012*
9	0.0017928328	*0.189448641*	**0.199721573**
10	0.0035786582	*0.378156808*	*0.398662519*
11	0.0000000019	*1.98238.10^{-7}*	*2.08988.10^{-7}*
14	0.0081798313	*0.864362775*	*0.911233209*
15	3.7879226851	*400.2697901*	**421.9745871**
16	1.0839622017	**114.5422859**	**120.7533893**
17	0.0050434434	*0.532940667*	*0.561839598*
20	0.0039361526	*0.415933241*	*0.438487395*

Column "Detector" represents the number code of detector, column "Alfa correlation" represents the parameter alpha, goal of PSO, column "Year1" represents the simulated measurement for the year 2015 and column "Year2" represents the simulated measurement for the year 2016.

The main goal of the study was finding alpha correlation numbers that, given equation 3, could represent a good evaluation of the real measurements. In equation 3, given $RE00_y$, the alpha correlation for each Detector that best represent the real measurements are presented in Table II.

In Table II, italic values are within the uncertainty range of real measurement of detectors. Bold values are outside uncertainty range. As the results show, 14 of 20 simulated values are within de uncertainty range and the other 6, even outside, they are very close de range limits of measurements.

14 of the 20 simulated values are perfectly matching the initial goal. But even the 6 not matching, are very close the outside limit of uncertainty range, showing the method chosen for the problem can perform well in radiation detectors simulation.

4. Conclusions

The study was made with the purpose of verifying viability of simulate radiation detectors in order to support ageing studies. The results with the proposed methodology show a promising path for solving this type of problem.

PSO algorithm was used in this study of optimization, new studies suggestions could be replicate this work with other optimization algorithms in order to compare the results and performances with different models.

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