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Test Intervals, cost and risk optimization in Nuclear Reactor Safety Systems Using Cuckoo Search Metaheuristic

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Technical Specifications (TSs) in the context of nuclear power plants are primarily focused on safety, ensuring that commercial nuclear reactors can safely shut down and mitigate the consequences of any postulated transient or accident. Thus, the TSs include requirements associated with safety in a systematically structured document, which describes the allowed outage time for each system component, as well as some fundamental human factors. In this context, the present work proposes a tool based on the Cuckoo Search (CS) metaheuristic to optimize the Test Intervals (TIs) of a simplified model of a High-Pressure Injection System (HPSI) of a Pressurized Water Reactor (PWR), considering the constraints and requirements established in the TSs. This study uses parameters such as test periodicity, hourly costs of testing, corrective maintenance, average test time, repair and corrective maintenance time, as well as the probabilities and failure rates of pumps and valves, in order to find an improved shutdown planning, including the simultaneous minimization of cost and unavailability. The results obtained in this study were compared with other metaheuristics from the literature, analyzing the effectiveness of each algorithm in converging to best solutions in the cost-risk trade-off. This comparative analysis shows that the developed methodology contributed not only to improving the standards of the TSs (Improved Standard Technical Specifications), but also that it can be an efficient tool for this class of problems.

Keywords: Nuclear safety, technical specifications, cuckoo search algorithm, test interval optimization, HPSI system, risk analysis.

1. Introduction

Optimizing the performance of systems and components is a primary industry goal, yet it faces significant challenges due to rigorous safety constraints and budgetary limitations. To address these complexities, Artificial Intelligence (AI) algorithms have become pivotal for enhancing performance de Souza et al. (2024); de Lima et al. (2008) and Lapa et al. (1999). In the nuclear sector, the application of these techniques has grown notably, covering areas from engineering design to maintenance strategies Caixeta et al. (2026); Alegrio and Nicolau (2025) and Lapa et al. (1999).

Technical Specifications (TSs) IAEA (1998) constitute the fundamental regulatory pillar for safe operation, establishing limits like the Allowed Outage Time (AOT) to ensure reactor safety NRC (2020); IAEA (2004). The industry seeks to optimize these requirements to increase operational flexibility and reliability, as highlighted by the Improved Standard Technical Specifications (ISTS) program Hoffman et al. (2004).

In this context, this work proposes a computational tool based on the Cuckoo Search (CS) metaheuristic to optimize Test Intervals (TIs) for the High-Pressure Safety Injection (HPSI) system. The approach mathematically models the problem, integrating TS constraints to balance the trade-off between reliability and cost Martorell and et al. (2006) and Wang et al. (2021). The CS algorithm is chosen for its efficiency in solving complex, non-linear problems, offering a robust solution for test planning under regulatory constraints Alegrio and Nicolau (2025) and de Mattos (2022).

2. Cuckoo Search

Cuckoo Search (CS) is an optimization algorithm inspired by the behavior of the cuckoo bird species, developed by Yang and Deb (2009). This bird exhibits parasitic reproductive behavior; that is, instead of building their own nests, cuckoos lay their eggs in the nests of other species, causing the host birds to incubate the eggs on their behalf.

The CS optimization algorithm begins with an initial population consisting of adult cuckoos and their eggs, which are laid in nests belonging to other birds. If these eggs are not recognized or rejected by the host bird, they survive and hatch into new individuals. The dynamics of egg survival and elimination establish the algorithm's selective mechanism: eggs representing infeasible or poorly adapted solutions are discarded, while higher-performing ones move toward more promising regions of the search space, generating new solutions. This evolutionary process is structured on the basis of three fundamental principles.

- Each cuckoo lays one egg at a time in a randomly chosen nest.
- The best nests, containing high-quality eggs (representing the best solutions), are carried over to the next generations.
- A fraction of the nests is discarded with a probability $P \in [0, 1]$, and new random nests are created within the search space to replace the discarded ones.

Thus, the algorithm's objective is to generate better solutions by replacing low-performing ones, aiming to optimize the objective function.

2.1. *Search space representation*

In optimization problems addressed by metaheuristic methods, solution representation is fundamental. Unlike Genetic Algorithms (GAs), in which solutions are commonly encoded as binary chromosomes, in Cuckoo Search (CS) the solution vectors are referred to as "nests."

Each nest constitutes a candidate solution to the problem, possessing the same dimensionality as the search space. For an N-dimensional problem, a nest is defined as a vector of real numbers representing a specific coordinate within the search space, as shown in Eq. (1):

$$Ninho = [x_1, x_2, \ldots, x_n] \tag{1}$$

Each component corresponds to a decision variable of the problem.

The fitness evaluation of a given nest is performed through the objective function. The relationship between the solution vector and its performance is expressed by Eq. (2):

$$f(Ninho) = f[x_1, x_2, \ldots, x_n] \tag{2}$$

2.2. *Lévy flight*

Lévy Flight constitutes a random walk model characterized by step lengths that follow a Lévy distribution. This movement pattern is observed in nature, specifically in the foraging behavior of various species, such as albatrosses. In the context of CS, as proposed by Yang and Deb (2009), the Lévy distribution is employed to simulate the new nest selection process, acting primarily in the optimizer's global search phase. Mathematically, the Lévy distribution can be expressed in a simplified form by a power law. Formally, the probability density function of the Lévy distribution is given by Eq. (3) and Eq. (4):

$$L(s, y, \mu) = \sqrt{\frac{y}{2\pi}} exp\left(-\frac{y}{2\,(s-\mu)}\right) \frac{1}{(s-\mu)^{\frac{3}{2}}} \tag{3}$$

$$L(s, y, \mu) = 0 \tag{4}$$

Where y represents a scale factor for the problem in question and $\mu > 0$ defines the minimum value for a step.

The step length S in a Lévy Flight can be obtained from Eq. (5):

$$S = \frac{u}{|\nu|^{\frac{1}{\beta}}} \tag{5}$$

Here u and ν are drawn from normal distributions with specific standard deviations. The Lévy Flight process involves choosing a random direction and generating this step, allowing for long jumps that sweep the search space.

2.3. *Evolutionary dynamics*

The search process begins with the generation of a population of n-dimensional nests. The evolution of solutions over the iterations in CS is governed by dynamics incorporating random walks. The position update of a nest x_i from generation t to generation $t+1$ is described by Eq. (6):

$$Ninho_i^{t+1} = Ninho_i^t + \alpha.Levy\,(\lambda) \tag{6}$$

In this formulation, the term α represents the step scale parameter. Within the scope of this work, a value of $\alpha = 1$ was adopted.

The development of the optimization model proposed in this work was carried out using the Python programming language (version 3.13). For the execution of vectorized mathematical operations and efficient matrix manipulation, the NumPy library (version 2.3.4) was employed.

3. Mathematical Models

In nuclear power plants, stakeholders have as one of their main objectives the minimization of maintenance costs or the risk associated with the nuclear plant, or both simultaneously. For some stakeholders, the primary focus lies in minimizing costs when carrying out maintenance activities, while complying with risk limits defined by regulatory authorities. However, for others, the objective is to minimize the risk of the nuclear plant under a constrained budget. To address these problems, it is necessary to establish mathematical models for cost and risk, particularly for safety systems; one possible approach is to consider maintenance activities.

In this contribution, the risk associated with a component or piece of equipment is reflected by its unavailability, which results from various factors such as failure on demand, random failure, test events, and both preventive and corrective maintenance. Consequently, the risk of a system is defined by its global unavailability Heo and Park (2010); Martorell et al. (2002).The annual cost of a component is decomposed into five categories: corrective maintenance cost, preventive maintenance cost, overhaul cost (due to the replacement of the component/equipment with a new one), testing cost, and outage cost (loss of electricity production). These costs are frequently determined by factors such as: hourly testing cost, hourly preventive/corrective maintenance cost, hourly cost of lost electricity production, mean time to restart a nuclear reactor, mean test time, mean maintenance time, among others Martorell et al. (2002); de Mattos (2022) and Alegrio and Nicolau (2025).

In this work, the unavailability and cost models employed are presented in Table 1.

The mathematical models for unavailability and cost utilize a set of parameters to quantify component reliability and operational costs. These parameters include: ρ is the probability of failure on demand; λ_0 denotes the residual failure rate of the component; α is the component aging factor; $\Psi(z)$ is the working condition factor; ε is the maintenance effectiveness, which varies within a defined interval; M represents the execution periods of scheduled activities; L is the interval for complete overhaul and replacement of the component with a new one; f_t, f_m, and f_c are the frequencies of test, preventive maintenance, and corrective maintenance activities, respectively; t and m correspond to the mean time spent on a test event and a preventive maintenance event; μ is the mean repair time of a component; D represents the Allowed Outage Time; T_s is the mean time required to restart a nuclear reactor following a shutdown; c_{ht}, c_{hm}, c_{hc}, and c_{hs} are the hourly costs associated with testing, preventive maintenance, corrective maintenance, and outage time, respectively; and c_r is the total cost to replace the component with a new one.

Given the mathematical models mentioned in Table 1, the unavailability of a system component

Table 1. Unavailability and cost models of a component Martorell et al. (2002).

Source of Unavailability	Mathematical Models
Unavailability due to random valve failures	$u_r(x) \approx \rho + \frac{1}{2}\left\{\lambda_0 + \frac{1}{2}\alpha M(\Psi(z))^2\left[1+(1-\varepsilon)\left(\frac{L}{M}-3\right)\right]\right\}$
Unavailability due to random pump failures	$u_r(x) \approx \rho + \frac{1}{2}\left\{\lambda_0 + \frac{1}{2}\alpha M(\Psi(z))^2\frac{1}{\varepsilon}(2-\varepsilon)\right\}$
Unavailability due to testing	$u_t(x) \approx f_t(x) \cdot t \cdot q_o^t$
Unavailability due to preventive maintenance	$u_m(x) \approx f_m(x) \cdot m \cdot q_o^m$
Unavailability due to corrective maintenance	$u_c(x) \approx f_c(x) \cdot \mu \cdot \left(1 - e^{-\frac{D}{\mu}}\right)$
Source of Cost	**Mathematical Models**
Testing cost	$c_t(x) = (t/T) \cdot c_{ht}$
Preventive maintenance cost	$c_m(x) = (m/M) \cdot c_{hm}$
Corrective maintenance cost	$c_o(x) = (1/L) \cdot c_r$
Overhaul cost	$c_c(x) = f_c(x) \cdot \mu \cdot \left(1 - e^{-\frac{D}{\mu}}\right) \cdot c_{hc}$
Downtime cost	$c_s(x) = f_c(x) \cdot e^{-\frac{D}{\mu}} \cdot T_s \cdot c_{hs}$

Source: Own elaboration.

can be expressed as the summation of the analyzed unavailabilities: $u(x) = u_r(x)+u_t(x)+u_m(x)+u_c(x)$. System unavailability can be expressed by approximating the combination of unavailabilities that can lead to system failure. In turn, this combination can be represented by the system's Minimal Cut Sets (MCS), where a minimal cut set signifies a minimal combination of component failures that results in system failure. Furthermore, for simplification purposes in this contribution, $U(x)$ is derived using a rare event approximation model, which serves as an upper bound based on its minimal cut sets. The mathematical expression is demonstrated in Eq. (7):

$$U(x) = \sum_i \prod_k u_{jk}(x) \tag{7}$$

In this expression, the summation over j encompasses the total number of Minimal Cut Sets (MCS) obtained after the reduction of the system structure. Meanwhile, the product over k covers the number of basic events associated with the corresponding MCS j. Furthermore, the term $u_{(jk)}$ represents the unavailability of the basic event k belonging to MCS j. Finally, x is a vector of variables regarding component test intervals, maintenance intervals, allowable downtime, etc.Similarly, the annual cost for a component can be expressed as $c(x) = c_t(x) + c_m(x) + c_c(x) + c_s(x) + c_0(x)$. Consequently, the cost model can be easily derived by summing the corresponding cost contributions of the relevant components, as shown in Eq. (8):

$$C(x) = \sum_i c_i(x) \tag{8}$$

Where c_i represents the annual cost for the i_{th} component.

Based on the system's risk and cost models, a single-objective optimization approach is proposed to regulate the test and maintenance activities of safety systems, focusing on minimizing unavailability. Furthermore, the total system cost must be less than or equal to a predetermined cost limit, and the decision variables of vector x must be within the defined range.

4. Case Study

To demonstrate the efficiency of the proposed integrated optimization method, it was used to plan maintenance strategies for a simplified model of the High Pressure Safety Injection (HPSI) system of nuclear power plants.

4.1. *Simplified HPSI model*

The HPSI is a crucial system applied in all PWR-type reactors, responsible for emergency cooling and coolant recirculation functions. Furthermore, it is vital for maintaining the water volume in the reactor core and ensuring adequate residual heat removal capacity following a Loss of Coolant Accident (LOCA). The HPSI is also automatically activated by danger signals (low pressurizer pressure, high containment pressure, etc.), indicating that other abnormal events besides LOCA can trigger it. Figure 1 shows the diagram of the simplified HPSI; it comprises 3 pumps and 7 valves.

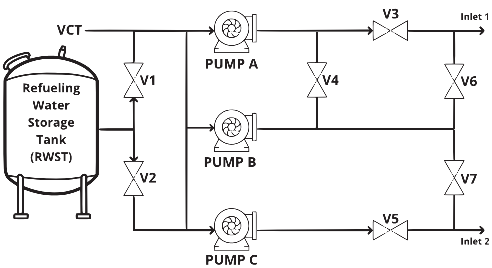

Fig. 1. Simplified HPSI (adapted from HARUNUZZAMAN and ALDEMIR (1996).

Following the occurrence of a Loss of Coolant Accident (LOCA), the HPSI acts by supplying high-pressure water to the Reactor Coolant System (RCS). In this situation, the HPSI draws coolant from the Refueling Water Storage Tank (RWST), injected with boric acid from the Boron Injection Tank (BIT), discharging it into the RCS cold leg. Flow occurs primarily through injection paths 1 (V1-PA-V3) and 2 (V2-PB-V5). Thus, pump PB and Valves V4, V6, and V7 are arranged to provide alternative flow routes and ensure system operation in case of failure in the normal paths.

For the analysis, the component and equipment test plans were grouped into three different strategies: strategy 1 applies to V1 and V2; strategy 2 covers V3, V5, and PA, PB, PC; and V4, V6, V7 belong to strategy 3. Regarding maintenance strategies, valves V1-V7 are grouped into one category, and pumps PA, PB, and PC into another. The imposed constraint assumes that all components in the same group will adopt the same test interval after optimization, although this does not necessarily mean that all are tested simultaneously. The test and maintenance parameters of the components/equipment, cited from the reference Martorell et al. (2002), are presented in Tables 2 and 3, and the cost information for these activities is in Table 4.

As previously mentioned, nuclear power plant stakeholders aim to establish a maintenance strategy that minimizes failure risk under a cost constraint or minimizes total cost under an acceptable risk constraint. To achieve this optimal design, it is fundamental to optimize the decision variable vector x, which governs test and maintenance activities. This vector, defined as x=$(T^1, k_2, k_3, M^1, n_1, M^2, D_1, D_2)$, includes the following parameters: T^1 is the test interval; M^1 and M^2 are the maintenance intervals; k_2, k_3 and n_1 are the constraint coefficients defining the sequential relationships between test and maintenance activities; and D_1 and D_2 are the allowable downtimes for the valves (V1-V7) and pumps (A, B, and C), respectively. For the valves, the allowable range is: $3h <= D_1 <= 24h$, and for the pumps, the allowable range is: $3h <= D_2 <= 24h$.

4.2. *Fitness function*

The CS algorithm was implemented to optimize the parameters applied in the unavailability and cost equations for analysis within the objective function. Consequently, two fitness functions were developed. The first objective function focuses on minimizing unavailability subject to a fixed cost constraint. Thus, a solution is penalized if its cost value exceeds 2743,99, a reference value from the literature Martorell et al. (2002), as shown in Eq. (9):

$$fitness = \begin{cases} U(x) \times 10, & \text{if } C(x) > 2743.99 \\ U(x), & \text{otherwise} \end{cases} \tag{9}$$

Therefore, if the solution's cost exceeds the constraint, it is penalized by multiplying the unavailability value by 10; otherwise, it retains the

Table 2. Test interval constraints (Martorell et al., 2002).

Test Interval	Valves	Pumps	Relation	Limits
T^1	V1, V2	-	-	168 h $\leq T^1 \leq$ 8760 h
T^2	V3, V5	PA, PB, PC	$T^2 = k_2 \cdot T^1$	$1 \leq k_2 \leq 10$
T^3	V4, V6, V7	-	$T^3 = k_3 \cdot T^2$	$1 \leq k_3 \leq 10$

Source: Own elaboration.

Table 3. Preventive maintenance interval constraints (Martorell et al., 2002).

Maintenance Interval	Valves	Pumps	Relation	Limits
M^1	V1, V2, V3, V4, V5, V6, V7	-	$L^1 = M^1 \cdot n_1$	$2 \leq n_1 \leq 20$ 720 h $\leq M^1 \leq$ 25920 h
M^2	-	PA, PB, PC	-	720 h $\leq M^2 \leq$ 25920 h

Source: Own elaboration.

Table 4. Component cost parameters (Martorell et al., 2002).

Equipment	$C_{ht}(\$/h)$	$C_{hc}(\$/h)$	$C_{hm}(\$/h)$	$C_r(\$)$	$C_u(\$)$
Valve	20	15	15	120	1500
Pump	20	15	15	360	1500

Source: Own elaboration.

original unavailability value. To select this penalty factor, a sensitivity analysis was conducted using values of 10, 10^3, 10^6, and 10^9; the selected value yielded the best results. Conversely, the second function focuses on minimizing cost subject to a risk threshold. Thus, a solution is penalized if the risk exceeds the limit of $3,630518x10^-4$. The penalty is applied by multiplying the cost by 10^3, as shown in Eq. (10). To select this penalty factor, the same sensitivity test was performed as before.

$$fitness = \begin{cases} C(x) \times 10^3, & \text{if } U(x) > 3,63x10^-4 \\ C(x), & \text{otherwise} \end{cases} \tag{10}$$

4.3. *Parameter definition*

Parameter tuning plays a crucial role in the performance of the CS algorithm. It is essential for the algorithm to exhibit strong exploration capabilities in the early stages and exploitation in the later stages. To determine the parameters, tests were conducted by varying the number of particles (nests) among 20, 50, and 100; the discovery probability (p_a) ranging from 0 to 0.5 with steps of 0.05; and the number of generations alternating between 50 and 100. The best results were obtained with the parameters shown in Table 5.

Table 5. CS algorithm parameters.

Number of Particles	Discovery Probability (p_a)	Number of Generations
50	0.05	100

Source: Own elaboration.

5. Results

The best result obtained using the proposed methodology for the objective function that minimizes risk can be observed in Table 6. In addition,

Table 6 presents the results reported by Martorell and the reference values Martorell et al. (2002), in order to compare and validate the developed method..

Table 6. Comparison of results for risk minimization.

Variable	Standard	CS	Martorell
T^1	2184	490,32	504
k_2	1	3,96	4
k_3	1	8,82	8
M^1	4320	6003,41	7920
n_1	20	2,01	3
M^2	4320	15480,13	8640
D_1	8	15,49	11
D_2	72	79,22	36
$U(x)$	$3,63 \times 10^{-4}$	$2,69 \times 10^{-5}$	$2,91 \times 10^{-5}$
$C(x)$	2743,99	2734,11	2741,86

Source: Own elaboration.

The results in Table 6 demonstrate the robustness of the Cuckoo Search (CS) algorithm in solving reliability optimization problems. The proposed method achieved the dominant solution, simultaneously attaining the lowest unavailability (2.69×10^{-5}) and the lowest cost (2734.11). Compared to the reference approach by Martorell et al. (2002), the CS algorithm identified a more efficient maintenance strategy, characterized by increased surveillance test frequency (T^1) while extending the preventive maintenance intervals for the pumps (M^2), thereby ensuring higher availability of the HPSI system with lower financial expenditure.

For a fitness that minimizes cost, the best results found are shown in Table 7.

The analysis of the cost minimization scenario highlights the superior economic efficiency of the Cuckoo Search (CS) algorithm, which achieved a global minimum cost of 586,64 representing a roughly 79% reduction compared to the Standard strategy and nearly half the cost of the solution reported by Martorell et al. (2002). Unlike previous conservative methods, the CS algorithm exhibited intelligent optimization behavior by utilizing the entire allowable safety margin, maintaining unavailability (3.62×10^{-4}) just below the constraint limit to maximize financial savings through the strategic extension of preventive maintenance intervals to over 25,000 hours.

Table 7. Comparison of results for cost minimization.

Variable	Standard	CS	Martorell
T^1	2184	2455,30	672
k_2	1	6,00	5
k_3	1	5,97	2
M^1	4320	25819,73	8640
n_1	20	2,08	5
M^2	4320	25419,53	8640
D_1	8	20,38	22
D_2	72	136,50	148
$U(x)$	3.63×10^{-4}	$3,62 \times 10^{-4}$	2.91×10^{-5}
$C(x)$	2743.99	586,64	1050,28

Source: Own elaboration.

6. Conclusion

This study proposed and validated a computational tool based on the Cuckoo Search (CS) metaheuristic to optimize surveillance test intervals and maintenance strategies in nuclear safety systems. Using the High-Pressure Safety Injection (HPSI) system as a case study, the approach successfully integrated complex reliability models with rigorous constraints derived from Technical Specifications.

The comparative analysis demonstrated the superiority of the CS algorithm over standard industry practices and reference results from the literature Martorell et al. (2002). In the risk minimization scenario, the CS algorithm identified a strategy capable of reducing system unavailability to 2.69×10^{-5}, an order of magnitude lower than the standard value, while simultaneously reducing costs. Conversely, in the cost minimization scenario, the algorithm exhibited high efficiency in exploring the feasible region, achieving a cost reduction of approximately 79% (from 2743.99 to 586.64) by strategically extending preventive maintenance intervals without violating safety limits.

These results indicate that current Technical Specifications may be conservative and that there is significant margin for economic optimization without compromising reactor safety. The proposed methodology supports the transition towards Risk-Informed Technical Specifications, providing operators with a robust decision-making tool.

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