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Title: Advanced Computational Algorithms for Designing and Dynamically Maintaining Industrial Systems: An NSGA-II Algorithm and Discrete Event Simulation Approach

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Abstract: Profit maximisation is an important objective for industries in a competitive world, and this can be achieved by improving the reliability, availability and life cycle cost (LCC) performance of repairable industrial systems. Engineers have used many techniques to improve the availability of these systems, such as adding redundant devices, using components that perform better in terms of reliability and maintainability, or programming dynamic maintenance strategies. However, the idea of using these techniques simultaneously has not received sufficient attention. The authors of this paper have recently studied the simultaneous optimisation of system design and maintenance strategy in order to achieve both maximum reliability and minimum life cycle cost: the Non-dominated Genetic Sorting Algorithm II (NSGA-II) has been coupled with event simulation to obtain a set of non-dominated solutions. In this work, this study is extended to the optimisation problem with three objectives, namely reliability, unavailability and life cycle cost. This combinatorial approach is successfully demonstrated through an industrial case study providing non-dominated solutions that balance reliability, system unavailability and life cycle costs, thus contributing to informed decision making in the choice of system configuration and specifications and its maintenance policy in competitive environments.

Keywords: Multi-objective evolutionary algorithms, Discrete Event Simulation, Reliability, Unavailability, LCC, Design, Maintenance.

1. Introduction

Repairable industrial systems face major challenges in terms of availability, reliability, and Life Cycle Cost (LCC). Their improvement relies on two key levers: design optimization and the definition of appropriate maintenance strategies, particularly dynamic maintenance (Liu et al. 2022).

However, few studies address the simultaneous optimization of these levers within a multi-objective framework. This gap stems from the lack of integrated methods capable of modeling, from the design stage, the actual system behavior and its interaction with logistical support. Despite recent advances, significant limitations remain regarding life cycle cost integration (Cacereño et al. 2024), repairability (Benfriha et al. 2024) maintenance action typologies (Adjoul, Benfriha, El Zant, et al. 2021), and performance objectives (Abouei Ardakan and Rezvan 2018). These challenges are further amplified by the stochastic and dynamic nature of failure and maintenance processes, which require robust modeling and optimization tools.

The proposed approach aims to integrate design and maintenance within a global framework, combining LCC (Greiner and Cacereño 2024), repairability (Adjoul, Benfriha, Zant, et al. 2021), types of maintenance actions (Cacereño et al. 2024), and operational availability (Benfriha et al. 2024). The objective is to achieve a more realistic global model that aims to maximize the reliability of industrial systems while minimizing unavailability and LCC.

For complex systems, performance indicators generally cannot be evaluated analytically. Stochastic simulation methods, such as Monte Carlo Simulation (MCS) and Discrete Event Simulation (DES), are therefore used to model failure and maintenance processes. Coupled with multi-objective evolutionary algorithms, particularly NSGA-II, they allow efficient exploration of complex solution spaces and identification of optimal trade-offs between reliability, unavailability, and LCC (Benfriha et al. 2021).

In this work, we propose a two-level integrated hierarchical optimization approach. The upper level (Macro) is dedicated to the joint optimization of design and maintenance strategy, considering reliability, maintainability, redundancy, monitoring, and MFOP duration parameters. At this level, MCS is used to generate component-level failure and repair scenarios, while DES models dynamic interactions and the overall system behavior over its entire life cycle. The lower level (Micro) determines, for each shutdown, the maintenance actions to be performed, such as component repair or replacement. The results of this level are fed back into the Macro level in order to update recovery periods and overall system performance.

The remainder of the paper is organized as follows: Section 2 presents the formulation and the method for joint optimization of design and maintenance. Section 3 describes the mathematical models used to evaluate system performance. Section 4 introduces the dynamic behavior modeling of the system. Sections 5 and 6 discuss a case study and results. Finally, section 7 concludes the paper.

2. Problem formulation and resolution

2.1. Problem formulation

The optimization problem considers three objective functions: the average Reliability $\mathrm{R}_{\mathrm{sys}}^{\mathrm{men}}(X)$, the average Unavailability $\mathrm{U}_{\mathrm{sys}}^{\mathrm{men}}(\mathrm{X})$, and the average Life Cycle Cost $\mathrm{LCC}_{\mathrm{sys}}^{\mathrm{men}}(\mathrm{X})$. The objective is to determine the optimal decision vector X=(Y,Z), combining design and maintenance parameters.

The vector Y groups, for each component i, the design parameters: reliability Ri, maintainability Mi, redundancy Pi, the presence of sensors Si, the availability of technical documentation Di, as well as the duration of maintenance-free operating periods l_{MFOP}. The vector Z describes the maintenance actions $[\mathrm{MA}_{\mathrm{ij}}]$ (no action, repair, replacement, inspection) applied to component i during shutdown j, over the system life horizon L_{s}. Each shutdown t_{j} corresponds either to the end of an MFOP period (preventive maintenance) or to a failure (corrective maintenance) at the system level.

The problem is subject to a set of constraints aimed at limiting the search space to feasible solutions. These constraints concern the domains of the decision variables and the investment costs of the components. The variables may be continuous or discrete, depending on the selected encoding. The problem can then be written as:

$$\text{Minimiser}\left\{ -R_{sys},\ U_{sys}\ ,LCC_{sys} \right\}$$

$$\text{subject to}\begin{cases} C_i \le C_i^{max} \\ R_i^{min} \le R_i \le R_i^{max} \\ M_i^{min} \le M_i \le M_i^{max} \\ l_{MFOP}^{min} \le l_{MFOP} \le l_{MFOP}^{max} \\ P_i \in \{0,1,2,3\} \\ S_i \in \{0,1\} \\ D_i \in \{0,0.2,0.5\} \\ MA_{ij} \in \{0, 1/2, 1/5, 1\} \\ 0 < t_j \le \mathrm{L_s} \\ i = 1, 2, \dots, n_{sys} \\ j = 1, 2, \dots, n_{MS} \end{cases} \tag{2}$$

where C_i^{max} is the maximum investment cost of component i, R_i^{min} et R_i^{max} respectively represent the minimum and maximum bounds of reliability (in terms of mean time to failure, MTTF) for component i, M_i^{min} et M_i^{max} respectively represent the minimum and maximum bounds of maintainability (in terms of mean time to repair, MTTR) that component i may have; t_j is the date of shutdown j, n_{sys} is the number of system components and n_{MS} is the number of maintenance shutdowns during the life cycle L_s.

2.2. Solution method

The problem resolution is based on a two-level hierarchical optimization approach, relying on multi-objective evolutionary algorithms of the NSGA-II type (Fig. 1).

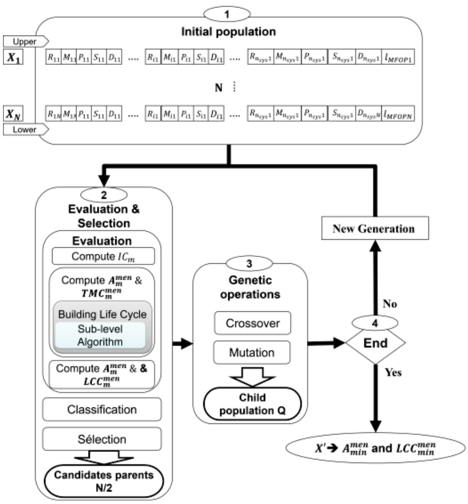

Fig. 1. Operating process of the hybrid algorithmic optimization method.

The Macro level jointly optimizes the design parameters, including reliability, maintainability, redundancy, monitoring, documentation, and maintenance parameters, including the system MFOP duration. The evaluation of solutions is carried out through life cycle simulation, integrating operating and maintenance phases. For each generated design solution, a Micro level is executed to dynamically optimize maintenance actions at each shutdown, whether planned or unplanned, by minimizing operational unavailability.

The performance outcomes from the Micro level are fed back into the Macro level for the computation of the objective functions, notably R_{sys}, U_{sys} , LCC_{sys}. This coupling enables efficient exploration of trade-offs between design and maintenance over the entire L_s.

3. System performance evaluation models

3.1. Total operational reliability evaluation model of the system

In this work, the operational Reliability of the system, denoted $R_{sys}(L_s)$, is defined as the average of the system survival probabilities over all MFOP. This approach, adopted in (Adjoul, Benfriha, Zant, et al. 2021), is based on the fact that the system performs a sequence of missions composed of successive MFOP periods. Its mathematical formulation is given by:

$$R_{sys}(L_s) = \frac{\sum_{j=1}^{n_{MS}} MFOPS_{sys_j}}{n_{MS}} \quad (3)$$

where $MFOPS_{sys_j}$ is the Maintenance-Free Operating Period Survivability (MFOPS). This metric measures the probability that the system survives during the MFOP duration, given that it was operational at the beginning of the period, taking into account the available information $H_{i,t_{(i=1,..,n_{sys})}}$ at time t_j. When the MFOPs are equal, with duration l_{MFOP}, its computation is given by:

$$MFOPS_{sys_{j_{1\le j\le n_{MS}}}} = \frac{R_{sys}(t_j + l_{MFOPj}/H_{i,t_{(i=1,..,n_{sys})}})}{R_{sys}(t_j/H_{i,t_{(i=1,..,n_{sys})}})} \quad (4)$$

where ($R_{sys}(t_j + l_{MFOPj})$) and ($R_{sys}(t_j)$) are the system reliabilities at the end and at the beginning of period j, respectively, given the available information $\mathrm{H}_{\mathrm{i,t}_{(i=1,..,n_{sys})}}$ at t_j.

To evaluate the reliability of a multi-component system over L_s, the first step consists in assessing the reliability of each component over this interval, given the available information on its state. Then, according to its functional structure (series, parallel, or combination), derived from the design model based on the reliability block diagram, the evaluation of the system reliability $R_{sys}(t)$ can be established.

3.2. Total operational unavailability evaluation model of the system

In this work, as in the studies of ((Greiner and Cacereño 2024)), the evaluation of operational Unavailability, denoted $U_{sys}(L_s)$, is based on a simulation approach, allowing the variability of times to failure and corrective and preventive maintenance durations to be taken into account. Times to failure (TF) and repair times (TR) are randomly generated from appropriate probability distributions, while preventive maintenance is modeled through the concept of MFOP. The Maintenance Recovery Period (MRP) integrates both maintenance actions (repair, replacement, inspection) and associated logistical delays. In this framework, the system $U_{sys}(L_s)$ over its life cycle L_s, composed of n_{MS} missions, is expressed as (Fig. 2):

$$U_{sys}(L_s) = \frac{\sum_{j=1}^{n_{MS}} \mathrm{U}_{\mathrm{sys_j}}}{n_{MS}} = \frac{\sum_{j=1}^{n_{MS}} \frac{\mathrm{MRP_{sys_j}}}{\mathrm{MFOP_{sys_j}}+\mathrm{MRP_{sys_j}}}}{n_{MS}} \quad (5)$$

where $\mathrm{MFOP_{sys_j}}$ and $\mathrm{MRP_{sys_j}}$ respectively indicate the maintenance-free operating periods (which may correspond to a period before a corrective or preventive maintenance shutdown) and the maintenance recovery periods (due to repair, replacement, or inspection) during mission j.

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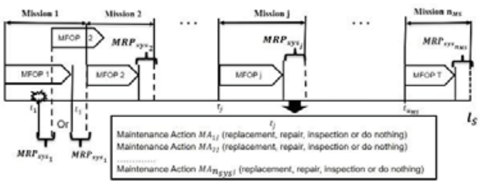


Fig. 2. Maintenance strategy decision process based on the MFOP concept.

4.3. System life cycle cost evaluation model

In this manuscript, as in the works of (Adjoul, Benfriha, Zant, et al. 2021), the LCC of multi-component industrial systems is defined under limits on Initial Costs (investments) $\mathrm{C_I}$ and Total Maintenance Costs $\mathrm{C_{TM}}$. Its mathematical expression is:

$$LCC(L_s)_{sys} = \mathrm{C_I} + \mathrm{C_{TM}}(L_s) \quad (6)$$

The initial costs of the system are given by:

$$\mathrm{C_I} = \sum_{i=1}^{n}(C_i + S_i\, SC_i + \delta D_i DC_i) \quad (7)$$

where $\mathrm{C_i}$ is the cost of component i, $S\mathrm{C_i}$ represents the cost associated with the sensors available on component i, δD_i is a Boolean equal to 1 if component i is provided with documentation and 0 otherwise, and $\mathrm{DC_i}$ is the cost of the technical documentation supplied for component i.

The discounted $\mathrm{C_{TM}}$ is expressed as the sum of the costs of preventive and corrective maintenance shutdowns, discounted to their dates of occurrence:

$$\mathrm{C_{TM}}(L_s) = \sum_{k=1}^{n_{ps}} \frac{C_{prev_k}}{(1+\nu)^{tp_k}} + \sum_{q=1}^{n_{cs}} \frac{C_{cor_q}}{(1+\nu)^{tc_q}} \quad (8)$$

where ν is the discount rate, Cprev_k and Ccor_q are the undiscounted costs of preventive and corrective maintenance, and tp_k and tc_q are their respective occurrence dates.

5. Modeling of system behavior over its life cycle

The modeling of system behavior over its life cycle, an integrated step of the approach described in Section 2, makes it possible to simulate the succession of MFOP and MRP (Fig. 2). Based on the design choices defined at the macro level (components, architecture, MFOP), the $\mathrm{l_{MFOP}}$ are generated, while optimization of the maintenance plan at the micro level determines the actions to be performed and the MRP. The alternation of these phases is modeled through a DES at the system level, considered as a set of components. For each component, times to failure (TF) and repair times (TR) are simulated using the MCS in order to account for variability in operating conditions.

The detailed process for modeling the system life cycle is described as follows:

1. Define the target life cycle duration L_s of the system and its components.
2. Optimize, via the NSGA-II (Macro level), the design parameters, including the MFOP length L_{MFOP}, as well as the reliability and maintainability functions of the components.
3. Initialize the system life cycle L_s (time t=0).
4. Randomly generate (TF) and (TR) for each component using their respective reliability and maintainability functions within a MCS.
5. Repeat the generation steps for all components.
6. Determine the system failure times TF_{sys_d} as a function of the system architecture and individual component failure times.
7. Initialize the system MFOPs and MRPs.
8. If TF_{sys_d} > (t+$\mathrm{l_{MFOP}}$), consider $\mathrm{l_{MFOP}}$ as the effective operating duration for this mission.

9. If $TF_{sys_d} \leq$ (t+l_{MFOP}), the MFOP is truncated to $(TF_{sys_d} - t)$, and the next system stop is updated.
10. Update the mission time t+l_{MFOP}.
11. If t≥L_s, no further maintenance action is performed ([MA_{ij}]=[0]).
12. If t<L_s, the Micro level proposes a set of maintenance actions [MA_{ij}] to prepare the next mission of length l_{MFOP}.
13. If the MFOP is fully completed, the MRP is calculated as:

$$MRP_{sys_j} = \delta MS_j * (\sum_{i=1}^{n_{sys}} TR_{ij}\ MA_{ij} * (1 - D_i) + Dlogp) \quad (9)$$

where δMS_j is a Boolean equal to 1 if there is a maintenance shutdown during mission j, and 0 otherwise, TR_{ij} is the repair time of component i during shutdown j; MA_{ij} is a decision variable of the four-state maintenance model (1, 1/2, 1/5, 0): 1 if component i is repaired during maintenance shutdown j, 1/2 if the component is replaced by an identical new component, 1/5 if the component is inspected when it does not have a sensor, and 0 if no action is taken; D_i is a design variable representing the percentage gain in maintenance duration when technical documentation is used for component i; and $Dlogp$ is the logistics time associated with the scheduled maintenance shutdown.
The associated C_{prev_k} is given by:

$$C_{prev_k} = \delta MS_j * (\sum_{i=1}^{n_{sys}} \left((C_i * \delta_{i,k}\right) + (TR_i * (1 - D_i) * \tau_O * \text{Ɣ}_{i,k})) + C_{plog}) \quad (10)$$

where $\delta_{i,k}$ is a Boolean equal to 1 if component i is replaced during preventive maintenance shutdown k, and 0 otherwise; τ_O is the hourly labor rate; $\text{Ɣ}_{i,k}$ is a four-state variable (1, 1/2, 1/5, 0) indicating whether component i is repaired, replaced, inspected, or left without action during preventive maintenance shutdown k, respectively; and $C_{log,p}$ is the logistics cost associated with preventive maintenance shutdowns.
14. Otherwise, in the event of a failure, the MRP is calculated as:

$$MRP_{sys_j} = \sum_{i=1}^{n_{sys}}((TR_{ij}\ MA_{ij} * (1 - D_i)) + (D_{UD_i} * (1 - S_i))) + Dlogc \quad (11)$$

where S_i is a design variable equal to 1 if component i is equipped with a sensor and 0 otherwise; D_{UD_i} is the diagnostic duration of component i; and $D_{log,c}$ is the required logistics duration. Thus, the diagnostic duration is considered only during unplanned system shutdowns for non-monitored components, since during scheduled shutdowns, components undergo maintenance actions known in advance.
The C_{cor_q} is evaluated by:

$$C_{cor_q} = \sum_{i=1}^{n_{sys}}((C_i * \delta_{i,q}) + (\tau_0 + \tau_{immob}) * TR_i * (1 - D_i) * \text{Ɣ}_{i,q}) + (C_{clog} + (D_{clog} * \tau_{immob})) + (C_{UD_i} + \left(D_{UD_i} * \tau_{immob}\right)) * (1 - S_i)) \quad (12)$$

where $\delta_{i,q}$ is a Boolean equal to 1 if component i is replaced during corrective maintenance shutdown q, and 0 otherwise; τ_{immob} is the cost of lost production per hour of system downtime; $D_{log,c}$ is the logistics duration associated with the corrective maintenance shutdown; $C_{log,c}$ is the logistics cost associated with the corrective maintenance shutdown; $\text{Ɣ}_{i,q}$ is a four-state variable (1, 1/2, 1/5, 0) indicating whether component i is repaired, replaced, inspected, or left without action during corrective maintenance shutdown q, respectively; C_{UD_i} is the unit diagnostic cost of component i; and D_{UD_i} is the unit diagnostic duration of component i.

Note that $\text{Ɣ}_{i,k}$ and $\text{Ɣ}_{i,q}$ can be linked to MA_{ij} as follows:

- $\text{Ɣ}_{i,k} = MA_{ij}$ if maintenance shutdown j is preventive,
- $\text{Ɣ}_{i,q} = MA_{ij}$ if maintenance shutdown j is corrective.

Similarly, $\delta_{i,k}$ and $\delta_{i,q}$ can be linked to $\text{Ɣ}_{i,k}$ and $\text{Ɣ}_{i,q}$ respectively, as follows:

- $\delta_{i,k} = 0$ if $\text{Ɣ}_{i,k}$=(1 or 1/5 or 0)
- $\delta_{i,k} = 1$ if $\text{Ɣ}_{i,k}$=1/2,
- $\delta_{i,q} = 0$ if $\text{Ɣ}_{i,q}$=(1 or 1/5 or 0)
- $\delta_{i,q} = 1$ if $\text{Ɣ}_{i,q}$=1/2,

15. Update the time t=t+MRP

16. Repeat the entire process until the end of the system life cycle (t≥L_s).

Once the life cycle has been simulated for a given design solution, system performance is computed over the horizon L_s. To ensure robust estimation of these indicators, the life cycle is simulated m times using MCS (Lesobre et al. 2014). The average performances are then obtained as:

$$R_{\text{sys}}^{\text{men}}(L_s) = \frac{\sum_{b=1}^{m} TOR_{\text{sys}}(L_s)}{m} ; U_{\text{sys}}^{\text{men}}(L_s) = \frac{\sum_{b=1}^{m} \text{TOU}_{\text{sys}}(L_s)}{m} ; \text{C}_{\text{TM}_{\text{sys}}}^{\text{men}}(L_s) = \frac{\sum_{b=1}^{m} \text{C}_{\text{TM}_{\text{sys}}}(L_s)}{m} \quad (13)$$

Finally, the average LCC (objective 3) of the system solution generated by the Macro algorithm is calculated using Eq. (6).

5. Case study of a real complex system – the fluid injection system

The system under study is a fluid injection system composed of pumps (P) and valves (V), as shown in Fig. 3.

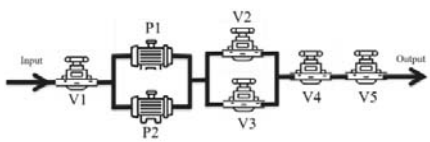


Fig.3. Real fluid injection system adopted from (Cacereño et al. 2023).

The input data used for the analysis combine sources from (Cacereño et al. 2023) and (Participants 2009). These data cover component reliability, maintainability, and costs (Table 1).

Table 1. Reliability, maintainability, and cost data of the reference system components (Participants 2009; Cacereño et al. 2023).

Parameters		Pump	Valve
C_i (units)		1.5	1
Ri	(TF λ) fails/h . 10^{-6}	159.57	44.61
	TFmax (h)	70 080	70 080
	TFmin (h)	1	1
Mi	TRμ (h)	9.5	9.5
	TRσ (h) =(TRμ–TRmin)/3		
	TRmax (h)= (TRμ+3·TRσ)		
	TRmin (h)	1	1
Di		0	0
Si		0	0

Table 2. Reference system data (Cacereño et al. 2023).

Parameters	Value
L_s (Life Span)	70 080 h
$\boldsymbol{\tau_O}$	0.125 units /h
$\boldsymbol{\tau_{immob}}$	0.5 units/h
l_{MFOP}^{max}	4,380 h
l_{MFOP}^{min}	2,190 h
$\mathbf{C_{log,p}}$	0.1 units
$\mathbf{C_{log,c}}$	0.15 units
$\mathbf{D_{log,p}}$	6h
$\mathbf{D_{log,c}}$	10 h
$\mathbf{D_{UD}}$	5 minutes
$\mathbf{C_{UD}}$	0.02 units /h

The system parameters are presented in Table 2.

Study assumptions

- Only two component states are considered: operational or failed.
- Components are mutually independent.
- Four maintenance modes: repair, replacement, inspection, do nothing.
- Immediate maintenance actions in case of failure.
- After repair, the component is restored to its initial state.
- Sensor installation: cost SCi=10% of the component cost.
- Provision of documentation and technician: cost DCi=15% and 30% of the component cost.
- Design parameters (Ri and Mi) may vary by ±50% relative to reference values.
- Maximum redundancy per component is limited to 3.
- Sensor installation provides only on/off state information when Si=1.

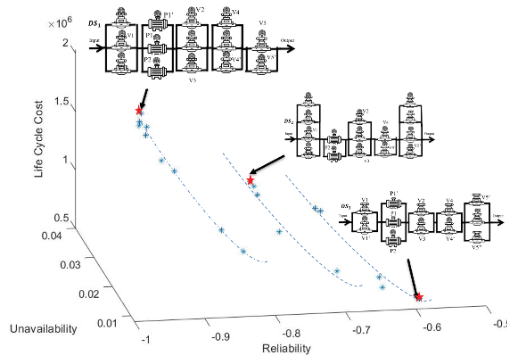
- Properties of redundant components are identical.
- Acquisition cost of a pump or a valve ≤ 10 units.

6. Results and discussion

Fig. 4 presents the Pareto front obtained from the multi-objective optimization of the system, simultaneously considering operational reliability, unavailability, and life cycle cost (LCC). Each point represents a non-dominated solution illustrating a specific trade-off between these conflicting objectives. The Pareto front highlights a general trend in which improvements in reliability are accompanied by an increase in LCC, reflecting the investments required for more robust system architectures, such as increased redundancy, condition monitoring integration, or enhanced maintenance strategies. Conversely, low-cost solutions are generally associated with lower reliability and higher unavailability.

The Pareto front also reveals three distinct dashed lines corresponding to clusters of solutions belonging to similar architectural families. Within a given cluster, system performance evolves progressively through incremental adjustments in design or maintenance parameters, whereas transitions between clusters reflect more significant structural changes in the system architecture. The representative solutions DS1, DS2, and DS3 clearly illustrate these trade-offs: DS1 prioritizes high reliability at the expense of cost, DS3 focuses on minimizing LCC with a controlled degradation of operational performance, and DS2 represents a balanced compromise between reliability, unavailability, and cost. These results confirm the relevance of the proposed optimization approach as a decision-support tool for selecting system configurations aligned with operational and economic priorities.

Fig. 4. Pareto front of optimal solutions in terms



of $R_{sys}^{men}(L_s)$, $U_{sys}^{men}(L_s)$ and $LCC_{sys}^{men}(L_s)$.

7. Conclusion

This paper presents the application of a methodology for the joint optimization of system design and opportunistic dynamic maintenance, based on the MFOP concept. The approach relies on coupling a two-level multi-objective evolutionary algorithm (NSGA-II) with DES and MCS, in order to simultaneously address the conflicting objectives of reliability, unavailability, and LCC.

The methodology was validated on a fluid injection system composed of two pumps and five valves. The results yielded a set of non-dominated solutions forming a Pareto front, showing that the optimized configurations improve reliability and availability while reducing the LCC compared to the initial configuration, under identical constraints.

The explicit integration of unavailability as a third objective, compared with previous studies, provides a more realistic analysis of the trade-offs between performance and cost and constitutes a relevant decision-support tool for guiding design choices. Future perspectives include extension to multi-state systems, exploration of other metaheuristics, and integration of inventory management into availability assessment.

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