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Enhancing the maintenance strategy and cost in systems with surrogate assisted multiobjective evolutionary algorithms

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A B S T R A C T

Digital twins need efficient methodologies to design maintenance strategies for decision-making purposes. Recently, a methodology coupling computational simulation and multiobjective evolutionary algorithms has been proposed for developing maintenance strategies consisting in assigning times for preventive maintenance activities and designing the layout of components of a system, minimizing the unavailability of the system and the strategy cost.

Here, surrogate assisted evolutionary algorithms (SAEAs) enhance the multiobjective optimization and improve the drawback of the computational cost of the maintenance strategy assessment based on discrete simulation. Several Kriging surrogates were tested.

Two industrial test cases are handled in the experimental section, where the methodology succeed in obtaining nondominated designs improving previous benchmarks, and enhancing state-of-the-art multiobjective optimizers, with up to an order of magnitude in terms of the number of fitness function evaluations. Results show that using multiobjective SAEAs in the development of optimal maintenance strategies could foster and improve digital twins operations.

1. Introduction

Reliability and safety of systems are highly related with industrial and civil infraestructure operation and management, and with their sustainability and resilience (Sun et al., 2020). Particularly, their maintenance and repair work assessment could be benefited both from first, computer aided-design and simulation, and second, from computational intelligence tools, in order to attain efficient and optimum engineering designs. Furthermore, Digital Twins (DT) require efficient methodologies and tools to design maintenance strategies for decision making purposes to ensure the continuity of operation of the physical entity (D'Amico et al., 2022). Recent research has highlighted the usefulness of using DT to support the development of maintenance strategies. When focusing on optimization, in (Chen et al., 2023) the role and function of machine learning for advancing of DT for predictive maintenance is exposed, explaining in this context the direct relationship between DT and optimization. The presence of DT has several key characteristics, among which are: a) the presence of DT allowing manufacturers to optimize operations virtually before implementing changes in real world and, b) the continuous improvement of DT through data collection, performance analysis and feedback for optimization.

Therefore, it is important for reliability engineers/decision makers to have efficient optimization tools that allow them to provide improved solutions in terms of system design, while minimizing unavailability and associated maintenance costs. In this line, a methodology combining discrete simulation and multi-objective evolutionary algorithms (EAs) has recently been published that allows obtaining optimal system designs from a multi-objective point of view (known as non-dominated solutions) with minimum unavailability and minimum maintenance costs (Cacereño et al., 2023). Each of the solutions automatically generated by this methodology selects the configuration of the system devices and, for each of them, its preventive maintenance strategy. Thus, the set of non-dominated solutions generated provides us with the set of solutions with minimum maintenance cost of the system for each value of unavailability of the system or, alternatively, the set of solutions with minimum unavailability of the system for each value of maintenance cost.

Optimization with EAs involves a high computational cost, as discussed in (Cacereño et al., 2021), which may be undesirable or even make the approach infeasible when solving engineering/real-world

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problems (Osaba et al., 2021). Therefore, the possibility of improving the computational cost of achieving the aforementioned system designs is a necessity, to which this research work aims to contribute by proposing, implementing and demonstrating an efficient methodology.

Improving the computational cost of obtaining such maintenance strategies is a necessary goal in order to provide decision makers with regularly updated information. To this end, in the field of reliability/maintenance/digital twins, this article proposes the combined use of surrogate modelling/metamodels with EAs, so called Surrogate Assisted Evolutionary Algorithms (SAEAs) -in particular, when multiobjective evolutionary algorithms are involved, they are specifically called Surrogate Assisted Multiobjective Evolutionary Algorithms (SAMEAs)-, to improve the above-mentioned multiobjective optimization of the maintenance strategy of systems. To the best of the authors' knowledge, this approach is a novelty in the field. Two benchmark industrial test cases of spray injection systems of a nuclear power plant safety system were solved in the experimental section, where the efficiency of several types of state-of-the-art surrogates were also compared and tested. The proposed SAMEA is able to succesfully improve the performance of a state-of-the-art multiobjective evolutionary algorithm with up to an order of magnitude in terms of the number of fitness function evaluations, or alternatively seen, even improve the quality of the final solutions with equivalent cost.

In section 2 a literature review and related works of digital twins (DTs) and the maintenance strategy, as well as the multiobjective optimization of the maintenance strategy, are introduced. In section 3, the surrogate assisted evolutionary algorithms are introduced. Next, in section 4, first the proposed surrogate assisted evolutionary algorithm in subsection 4.1, and second the method for evaluating the availability and cost of the system in subsection 4.2 were described, respectively. Then, in section 5 the test cases used in the experimental results and discussion section 6 were shown. Finally the paper ends with section 7, conclusions.

2. Literature review and related works

First, some recent literature covering DT and their relationship with the maintenance strategy of the physical system is shown in subsection 2.1. Next, a focused review of multiobjective optimization for the development of an adequate maintenance strategy is exposed in subsection 2.2.

2.1. Digital twins and maintenance strategy

Several review/survey and general works on DT were first cited, highlighting their main claims in relation to DT and maintenance. In (Chen et al., 2023), Boyes and Watson present an analysis framework of DT. They claim that changes promoted by the DT to the physical entity depend on the DT's purpose and the algorithms or models in use, and may include among others, modifications to operational use (e.g., duty cycle, frequency of maintenance, or recalibration). Among the functional components of DTs are the master and reference data, which may include the maintenance and support information (e.g.: date last inspected or tested, mean-time-to-failure, etc.). (Cimino et al., 2021) harmonises and integrates the major DT interpretations into the DT multiverse paradigm in terms of data integration and the establishment of consistency rules for data and models. Analysis and simulation performed by the DT may be used for decision-making purposes, including the maintenance to ensure continuity of operation and health of the physical entity.

Two literature review of DTs for maintenance are mentioned: 1) a literature review of DTs for maintenance could be read in (Errandonea et al., 2020) covering among the different maintenance strategies: reactive maintenance, preventive maintenance, condition-based maintenance, predictive maintenance, and prescriptive maintenance. They expose applications in the construction industry, naval engineering, manufacturing, energy industry, aerospace engineering, logistic services, hydraulic industry, automotion, railway industry and materials. It is claimed that DT have application in preventive strategies, where they are used to predict the condition of the asset to reduce the number of preventive maintenance activities and eliminate unnecessary ones, allowing longer time intervals between them. 2) in (D'Amico et al., 2022) a more recent review related with DT and maintenance clasify the application areas in manufacturing (machine tools, automotive), civil, infrastructures (power plants, buildings, renewable energy systems), transports, and food. They claim that the benefits of using DTs in maintenance found in the reviewed articles include among others, to increase the information available to help analytics and to enable a long-term vision to apply a cost-effective maintenance strategy.

Some recent relevant references related with maintenance and DT, classified by topics are presented as follows.

In the area of manufacturing, Soori et al. (2024) develop a comprehensive review of virtual manufacturing in Industry 4.0. They point to DT as a potential area of future research in Industry 4.0, enabling real-time monitoring and preventive maintenance. An artificial neural network (ANN) is proposed to predict the remaining lifetime of mechanical components, subjected to specific processing conditions. Using the ANN in a big-data system, active preventive maintenance is developed (Wan et al., 2017). Prognostic accuracy and reliability are improved by using DT-driven methods, providing a basis for decision making (Cui et al., 2023). Guo et al. (2021) provide a timing scheme to determine preventive maintenance at minimum cost by developing a maintenance strategy model based on the accurate remaining useful life (RUL) prediction. The RUL is established from a DT-based real-time prediction model.

In the energy field, Zhao et al. (2024), provide a comprehensive review of battery safety prognosis. They consider that deep reinforcement learning can be used for prognosis and smart health management to optimize battery preventive maintenance. Battery data needs to be integrated into virtual replicas of machines or systems as DT to explain complex physical behaviours. Ruliandi (2015) and Priyangga and Ruliandi (2018) developed ANN models to estimate the steam consumption coefficient of a geothermal power plant. They used temperature and pressure measurements from sensors. Due to natural wear and tear of the plant components, an increasing trend of the steam consumption coefficient over time is expected, which was replicated by the generated models. Such models can be used to plan the preventive maintenance of the plant. With regard to offshore wind farms (OWFs), preventive maintenance strategies integrated with condition monitoring are efficient in terms of reducing their Operational and Maintenance (O&M) costs and improving their reliability. The DT models proposed by academics can be used for predicting the remaining lifetime and failure monitoring of OWT components, as well as for supporting preventive maintenance (Xia and Zou, 2023).

In the building and construction sector (Dahiya and Laishram, 2024) Dahiya and Laishram propose a strategic framework for reducing energy demand in the building sector. To improve energy efficiency, they recommend the use of network enabled building management tools and control systems. They claim that the collection of data on current performance of building systems and maintenance levels, and the development of DT for new construction and major renovation projects, can be used for preventive and periodic maintenance of buildings, installations and equipment to extend their useful life. In (Arisekola and Madson, 2023), anomaly detection algorithms help managers to perform preventive maintenance. Madubuike et al. (Madubuike and Anumba, 2023) propose a DT that integrates virtual design/modelling technologies, sensors, data analytics techniques, communication networks, and mobile devices to monitor healthcare facilities in time and implement preventive maintenance. Among other indicators, the performance of the heating, ventilation and air conditioning system is monitored. Another review of machine learning methods applied to structural dynamics and vibroacoustic capabilities (Zaparoli Cunha et al., 2023) claims that the extraction and recognition of fault patterns from measurements in the time and frequency domains make Structural Health Monitoring (SHM) the most explored technique in the field. SHM allows early failure detection and prediction of RUL. Therefore, SHM provides useful methods for preventing catastrophic failures and implementing preventive maintenance schedules to optimize uptime and maximize the use of component lifetime. In (Badenko et al., 2021) the integration of DTs and building information models (BIM) to enhance the operation and maintenance stage of industrial facilities in the context of Factories of the Future has been fostered.

In transport, Arifur Rahman et al. (2024) claim that more sensors are being incorporated into infrastructure in applications related to railways, aircraft, civil structures or pipelines. The data obtained from the sensors are used for machine learning based diagnosis and prognosis to design preventive maintenance strategies. The simulation strategy realised by the DT of preventive maintenance supports the maturity and validation of the machine learning-based diagnostic and prognostic framework. Venkatesan et al. create an intelligent DT and propose a health monitoring and prognosis system for permanent magnet synchronous motor (Venkatesan et al., 2019). Predicting the life of the motor enables preventive maintenance to ensure its reliability and safety (Deng et al., 2023).

Finallly, in aeronautics, Attaran et al. (2024) claim that "Digital Twins technology allows aircraft engineers to schedule preventive maintenance, reducing the risk of in-flight emergencies and ensuring on-time departures and arrivals".

Benefits for the development of efficient DTs, were obtained when building methods capable of achieving optimized maintenance strategies. Digital twins are strongly related to the improvement and optimization of the systems in which they are involved. Thus, citing the review work on predictive maintenance based on DT technology (Zhong et al., 2023): "The digital twin has the characteristics of interactive feedback between cyberspace and physical space, data fusion and analysis, and decision-making iteration optimization". As stated there, predictive maintenance analyses feasibility, plans and implements maintenance based on condition monitoring, fault diagnosis and condition prediction, which is traditionally a manual process. DT enhances this with intelligent services such as design and operation optimization, fault prediction and diagnosis, enabling data processing for predictive maintenance and global optimization of maintenance decisions without manual timing selection. The result is a tool that automatically suggests optimal maintenance solutions.

In maintenance optimization, the objectives can generally be categorized as: minimizing maintenance costs, and maximizing availability/reliability (or equivalently minimizing unavailability) -which in case of power plants is directly related to minimizing production losses- (Wayan Ngarayana et al., 2019). By using a single objective optimization, maximum reliability is often used as a constraint parameter and the associated maintenance costs are minimized. However, it is possible to tackle the problem directly as a multi-objective problem by minimizing the maintenance cost and minimizing the unavailability simultaneously using evolutionary multi-objective algorithms (Cacereño et al., 2023), which are able to provide the set of non-dominated solutions (optimal from the multi-objective perspective) in a single run (Emmerich and Deutz, 2018). This set allows the decision maker to have the maintenance strategies that provide minimum maintenance cost solutions for each unavailability value, or alternatively, to have the minimum unavailability solutions for each associated maintenance cost value. This is a much more complete and efficient approach than that provided by single objective optimization where it would be necessary to perform an optimization process for each associated reliability constraint value, demonstrating the need and power of multi-objective optimization using evolutionary algorithms in the development of efficient maintenance strategies.

2.2. Maintenance strategy: multiobjective optimization

Having introduced the need and opportunity to approach the problem as a multi-objective optimization in subsection 2.1, this subsection reviews recent references to multi-objective optimization in the area of reliability and, in particular, maintenance strategy.

In (Cacereño et al., 2023) a methodology coupling EAs with discrete event simulation for minimizing simultaneously unavailability and maintenance strategy cost of systems was validated, in relation to systems design and their maintenance strategy. Particularly, the corrective and preventive maintenance were taken into account, consisting in achieving the optimum period of time to carry out a maintenance activity. Previously, many authors considered optimal system design or optimal maintenance strategy separately. Simultaneous optimization of systems' design and maintenance strategy has not been considered by many authors. This problem was first formulated by (Levitin and Lisnianski, 1999). Later, such a problem was solved using Markov processes (Nourelfath et al., 2012). However, in this work the use of Discrete Event Simulation was proposed since it allows the analysis of complex systems in a more realistic representation of their behaviour. Several industrial systems of increasing complexity with automatic selection of devices were succesfully optimized, including a comparison of seven state-of-the-art multiobjective evolutionary algorithms (including NSGA-II (Deb et al., 2002)) and a multiobjective swarm optimizer in a test case with up to seven devices (see Test Case 1 in section 5). The statistical significance results of the hypervolume metric (Emmerich and Deutz, 2018) showed that in this experiment, some decomposition based algorithms and the multiobjective swarm optimizer have worse performance than three dominated-based (NSGA-II among them), one indicator-based selection method and one decomposition-based selection method. No statistically significant differences in performance were observed among these five state-of-the-art methods.

A focused review for optimizing maintenance strategies and cost with EAs (single and multi-objective cases) in reliability problems was published in (Cacereño et al., 2021). The NSGA-II algorithm optimized a containment spray injection system (CSIS) of a nuclear power plant, based on a case proposed in (Greiner et al., 2003) comparing different encodings, crossover operators, parameter configurations and chromosome lengths in relation to accuracy levels when scheduling maintenance strategies. No difference in performance was found to be statistically significant.

In (Cheng et al., 2023) a multiobjective optimization model for the maintenance policy is built for redundant airborne systems operating with faults. An approach based on the NSGA-II algorithm is used to optimize the operating cost and the dispatch reliability by airlines, fostering aircraft safety. It is also compared with a decomposition based algorithm. The diversity of solution sets obtained with NSGA-II improves the results of the decomposition-based selection algorithm.

Bris et al. (Briš and Tran, 2023) minimize both unavailability and cost through the use of an optimal maintenance strategy, quantifying the unavailability of a complex system represented through a directed acyclic graph, solving the real fluid injection system adopted from reference (Cacereño et al., 2021); however, they do not use an automatic selection of devices in the optimization process, but an exhaustive approach.

In (Maneckshaw and Mahapatra, 2022) multiobjective evolutionary algorithms were applied to a reliability redundancy allocation model with constraints representing system complexity to enhance system reliability and to diminish its cost through a feasible redundancy in its stages. They propose a multiobjective evolutionary algorithm based on the non-domination criterion, but the results are not compared with state-of-the-art multiobjective evolutionary algorithms.

Among the research trends in real-world optimization with metaheuristics (which include evolutionary algorithms and bioinspired algorithms) in (Osaba et al., 2021) are: robust optimization and worst-case analysis, translation of real-world requirements into optimization problems, hybridization of mathematical tools with metaheuristic algorithms, metamodelling for real-world optimization, and automation of algorithm selection and parameter tuning. Thus, the fourth proposal relates to the use of metamodels or surrogate models in real-world optimization problems. Research on surrogate-assisted optimization has gained particular interest in recent years. As indicators: 1) it is covered in one of the InCites Essential Sciences Indicators of Clarivate as one of the research fronts (where, e.g. the reference (Jin et al., 2019) has been cited 228 times in the Web of Science database until January 2024); 2) a review article on surrogate-assisted evolutionary algorithms for expensive optimization problems published only three months before the submission of this manuscript (He et al., 2023), where a thorough review of real-world engineering applications was detailed, including 158 references. These include energy efficient design of buildings, aero-engine compressor aerodynamic design, and other applications as: engine manufacturing, ship design, automobile design, satellite design, wing optimization, antenna design, and energy and power. No references were found for maintenance strategy, reliability engineering, or digital twins. No citations were found after searching the Scopus and Clarivate Web of Science scientific databases.

In this research work we propose a new methodology in the context of reliability engineering/maintenance strategy optimization/digital twins, based on the combination of EAs (especially multiobjective EAs) and surrogate modelling to improve their efficiency (SAEAs). SAEAs constitute an unexplored opportunity to enhance the performance of a multiobjective optimized maintenance strategy as explained above. They and their advantages are described in the following section 3.

2.3. Literature review summary

From the literature review, it is clear that the use of DT is useful for informed decision making in relation to the various maintenance strategies defined in the literature in general and preventive maintenance in particular. The use of DT has been extended to different engineering fields and for different purposes in relation to the definition of the maintenance strategy to be followed. On the other hand, different criteria have traditionally been considered for optimizing maintenance (minimum cost, maximum availability, …). These criteria can be considered together or separately, the former being the most efficient and therefore the one followed in the present work. NSGA-II is one of the most widely used multi-objective optimization methods in the field of system reliability and has traditionally provided good solutions. The use of surrogate models is currently attracting a lot of interest and their application in the field of system reliability is non-existent, which represents an opportunity.

3. Surrogate assisted evolutionary optimization

Evolutionary algorithms (EAs) require to evaluate the fitness function many times, which could lead to a non-practical procedure if the available computational resources are not adequate, specially if the assesment of the objective function is computationally expensive. This case happens frequently when solving real world optimization problems. A way to reduce the number of required fitness functions is to use a surrogate model or metamodel which assists the optimization process (Greiner et al., 2017). EAs supported by this surrogate, are called surrogate-assisted EAs (SAEAs). Moreover, established methods using SAEAs to solve real world engineering problems are also known as Data Driven Evolutionary Algorithms (Jin et al., 2019).

Very recently, in (Bäck et al., 2023) Bäck et al. highlight eleven milestones of the development of EAs in the last 30 years. SAEAs to solve expensive objective function evaluations were one of them. There, the stablished use among the automotive, marine, aviation, and other engineering fields of SAEAs is claimed when solving computer-simulations (Mergos, 2022). They cite also the original idea of using surrogate models in optimization from the Efficient Global Optimization (EGO) framework (Bayesian optimization), from Jones et al. (1998).

Some historical reviews of surrogate-assisted EAs are in (Jin and Sendhoff, 2002), (Jin, 2003), (Jin, 2011). Surrogate models could influence population initialization, crossover, mutation and fitness evaluations. Several strategies for their use (model management: population-based, individual-based, and generation-based strategies) have been proposed.

In Osaba et al. (2021), the use of surrogate models is recommended as a practical alternative of a time reduced fitness function, as a way to reduce the time to obtain a reasonable good solution, as one of the research trends in real-world optimization with metaheuristics, as a tool to develop efficient metaheuristics for real-world problems, and finally, their hibridization with metaheuristics was highlighted as a prominent role in the field of real-world problems optimization. They also mention the use of DTs as a recent application of simulation environment that serve as a computational representation of large-scale complex systems. Their use constitutes a straightforward approach to circumvent an issue that appears concurrently in real-world problems: the impossibility of formulating objective functions and constraints in mathematical form; they are also able to account for the uncertainty present in non-deterministic application scenarios.

A survey of parallel surrogate assisted optimization was published in (Haftka et al., 2016).

Other recent reviews of SAEAs were published in (Jin et al., 2019), (Stork et al., 2019), which cover more recent developments as the use of SAEAs to solve multi-objective optimization problems. Several pioneering approaches of SAEAs for multiobjective optimization are the ParEGO algorithm in (Knowles, 2006), using local Gaussian random field metamodels in (Emmerich et al., 2006), and the MOEA/D-EGO in (Zhang et al., 2010) that is also assisted by Gaussian processes. In general, Gaussian processes/Kriging models provide a good approximation from a small amount of data. Other recent survey covering among others, multi-objective and many-objective SAEAs is found in (Jin et al., 2021).

4. Methods

4.1. SAEA description

Among the multi-objective SAEA methods, in this research we follow an approach similar to the one published in Galuzio et al. (2020). They introduce the multi-objective Bayesian optimization algorithm (MOBOpt), which integrates as optimizer a non-dominated ordering based state-of-the-art evolutionary multiobjective optimizer -the non-dominated sorting genetic algorithm NSGA–II–, and as surrogate a Kriging metamodel (Sacks et al., 1989) with a Matern correlation function (Genton, 2001).

Surrogate models using other correlation functions were explored in the current research, particularly, following description and implementation in (Bouhlel et al., 2019), (Saves et al., 2023). We apply the squared exponential (Gaussian), absolute exponential (exponential), Matern32 (this is the one originally suggested in (Galuzio et al., 2020)) and Matern52 correlation functions, all of them with a linear model of the deterministic term.

4.2. Reliability evaluation

In this section we introduce a brief explanation of the fitness functions, which are derived from the functionability profile of system. A brief background and overview of the methodologies employed for the assessment of system availability is presented below. Readers interested in a detailed account of the procedure for the construction of the functionality profile are directed to (Cacereño et al., 2023).

Andrews and Moss (2002) computed system Availability *(A(t))* using the unconditional failure $w(t)$ and repair $v(t)$ intensities. When a system undergoes a continuous failure and repair process, it presents a failure probability in time $[t, t+dt)$ given it was working at $t=0$. Such a failure probability is denoted by $w(t)dt$. The failure in time $[t, t+dt)$ takes place, on the one hand, because the system works continuously from 0 to t until the first failure in $[t, t+dt)$. In this case, the failure probability is given by $f(t)dt$, where $f(t)$ is the failure density function. On the other side, the system fails in time $[t, t+dt)$, but such a system has been repaired after failing in time $[u, u+du)$. The probability in this case, is given by $v(u)du \times f(t-u)dt$. Equation (1) explains all possibilities.

$$w(t)dt = f(t)dt + \int_0^t f(t-u)v(u)du\, dt \tag{1}$$

The repair only takes place in $[t, t+dt)$ when the failure occurs in time $[u, u+du)$ prior t. This probability is $g(t-u)dt \times w(u)du$, where $w(u)du$ is the failure probability in time $[u, u+du)$ given the system was working at $t=0$, $g(t-u)dt$ is the repair probability in time $[t, t+dt)$ given the system has been in faulty state since the last failure in $[u, u+du)$ and it was working at $t=0$. The repair density function is given by $g(t)$. Equation (2) can be obtained since u varies from 0 to t.

$$v(t)dt = \int_0^t g(t-u)w(u)du\, dt \tag{2}$$

When dt is cancelled from both Equation (1) and Equation (2), the simultaneous integral equations defining the unconditional failure and repair intensities can be obtained, as shown in Equation (3).

$$\begin{aligned} w(t) &= f(t) + \int_0^t f(t-u)v(u)du \\ v(t) &= \int_0^t g(t-u)w(u)du \end{aligned} \tag{3}$$

Availability can be obtained by solving the pair shown in Equation (3). Solving such a pair is really difficult when systems do not follow exponential failure and repair intensities (constant failure and repair rates). Therefore, a simulation approach can be followed in order to compute Unavailability (obtained as the opposite of Availability).

The evaluation of the first fitness function, Unavailability of the system at mission time, is assessed by Equation (4).

$$U = \frac{\sum_{j=1}^{m} t_{rj}}{\sum_{i=1}^{n} t_{fi} + \sum_{j=1}^{m} t_{rj}} \tag{4}$$

where n is the total number of operation times, t_{fi} is the i-th operation time in hours (Time To Failure or Time to Start following a scheduled Preventive Maintenance Activity), m is the total number of recovery times and t_{rj} is the j-th recovery time in hours (due to repair or preventive maintenance activity).

Here, economic cost is a variable directly associated with the recovery times, which are related to corrective and preventive maintenance activities. The evaluation of the second fitness function, Cost of the maintenance strategy, is computed by Equation (5).

$$C = \sum_{i=1}^{q} cc_i + \sum_{j=1}^{p} cp_j \tag{5}$$

where C is the system operation cost quantified in economic units, q is the total number of corrective maintenance activities, cc_i is the cost due to the i-th corrective maintenance activity, p is the total number of preventive maintenance activities and cp_j is the cost due to the j-th preventive maintenance activity.

5. Test cases

In a recent literature review on DT for maintenance (Errandonea et al., 2020), the energy industry is ranked second in number of references after the manufacturing industry –which is ranked first-; construction is ranked third. Also, in R. Van Dinter et al. (van Dinter et al., 2022), a systematic literature review on predictive maintenance using DT is presented, where among the application domains, energy is ranked second with 23.3% of references, after manufacturing. Energy applications include gas and oil industries, wind turbine management, and nuclear power plants.

Nuclear power plants, like oil rigs and aviation, fall into the category of high-risk industries (Pita, 2019). Their inherent nature requires strict regulation and continuous implementation of risk mitigation measures to maintain safety levels within acceptable bounds. Among the various risk mitigation methods, the role of adequate and timely maintenance is paramount. The largest operating cost in nuclear power plants is maintenance activities, where almost all nuclear power plant maintenance activities around the world are based on breakdown and time-based maintenance (Wayan Ngarayana et al., 2019). Therefore minimizing the maintenance cost becomes one of the most important things to make nuclear power plants competitive with other power plants (Matsuo et al., 2015).

The test cases dealt with in this work are based on real world systems in a nuclear power plant. They belong to a wide range of studies developed in the field of reliability and their interest is supported by several publications. They were first considered in (Greiner et al., 2003), a seminal publication in multiobjective optimization with evolutionary algorithms in the field of reliability engineering. In any case, it is worth mentioning that the proposed optimization methodology is applicable to other engineering fields, as long as the necessary models or data to build the functionability profile of the system devices to be considered are available. An example of test case in the field of substation automation systems can be found at (Cacereño et al., 2024).

The two test cases handled in the next results section 6 were taken as benchmarks from (Cacereño et al., 2023). They are stablished test cases supported by already published scientific reliability optimization literature. That is the main reason of the choice of those case studies, in order to guarantee validation and reproducibility of results. They represent models of a containment spray injection system (CSIS) of a nuclear power plant and are inspired by a similar structure analyzed in (Greiner et al., 2003). In order to wipe radioactive contamination that may be released after a loss of coolant accident, the CSIS aim is the injection of borated water into the containment.

A diagram of Test Case 1 is represented in Fig. 1. A diagram of Test Case 2 is represented in Fig. 2, where an additional parallel branch has been included. In both figures, cut valves are labeled with V_i and impulsion pumps are labeled with P_i.

The data set for the system devices of both test cases is shown in Table 1, including the information required by the building of the functionability profile in order to compute the fitness functions as defined in subsection 4.2. Definition of each parameter shown in this table is available in the Appendix.

Design variables define the period to perform a preventive maintenance activity for each of the potential system devices in both test cases (seven in Test Case 1 and fourteen in Test Case 2). They also define the presence or absence of a parallel pump P2 and a parallel valve V4 -in Test Cases 1 and 2-, and presence or absence of a parallel pump P9 and a parallel valve V11 -in Test Case 2-.

The non-dominated solutions sought are constituted by the values of the maintenance times of each device, and the structure of the

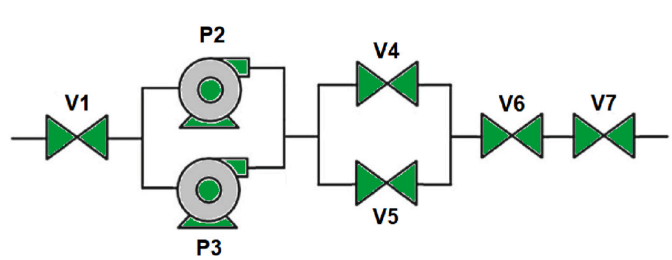

Fig. 1. Diagram of test case 1 (Cacereño et al., 2023).

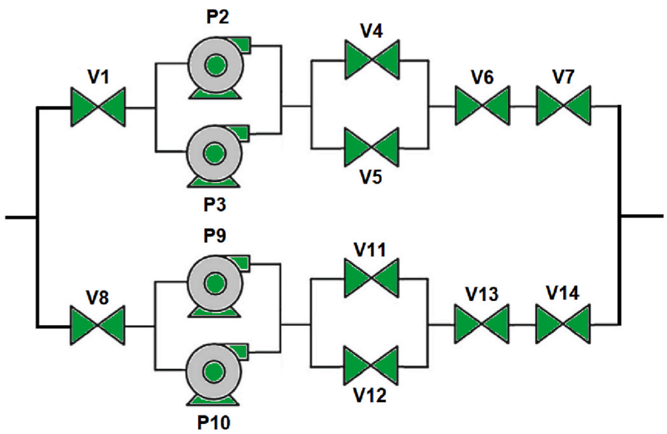

Fig. 2. Diagram of test case 2 (Cacereño et al., 2023).

Table 1
Data set for Test Cases 1 and 2, system devices (Cacereño et al., 2023). MRI refers to the Machinery and Reliability Institute, Alabama, USA.

Parameter	Value	Source
Corrective Maintenance Cost	0.5 units	MRI
Preventive Maintenance Cost	0.125 units	MRI
Pump TF_{min}	1 h	MRI
Pump TF_{max}	70,080 h	MRI
Pump TF λ	$159.57 \cdot 10^{-6}$ h	OREDA (OREDA, 2009)
Pump TR_{min}	1 h	MRI
Pump TR_{max}	24.33 h	$\mu + 4\sigma$
Pump TR μ	11 h	OREDA (OREDA, 2009)
Pump TR σ	3.33 h	$(\mu - \text{TRmin})/3$
Pump TP_{min}	2920 h	MRI
Pump TP_{max}	8760 h	MRI
Pump TRP_{min}	4 h	MRI
Pump TRP_{max}	8 h	MRI
Valve TF_{min}	1 h	MRI
Valve TF_{max}	70,080 h	MRI
Valve TF λ	$44.61 \cdot 10^{-6}$ h	OREDA (OREDA, 2009)
Valve TR_{min}	1 h	MRI
Valve TR_{max}	20.83 h	$\mu + 4\sigma$
Valve TR μ	9.5 h	OREDA (OREDA, 2009)
Valve TR σ	2.83 h	$(\mu - \text{TRmin})/3$
Valve TP_{min}	8760 h	MRI
Valve TP_{max}	35,040 h	MRI
Valve TRP_{min}	1 h	MRI
Valve TRP_{max}	3 h	MRI

components of the system devices, in order to both minimize the cost and minimize the unavailability of the system.

6. Results and discussion

In this section, first a general description of the procedure is presented in subsection 6.1. Next, results of Test Case 1 are introduced in subsection 6.2 and in subsection 6.3 results of Test Case 2 are shown. Finally the discussion section is exposed in subsection 6.4.

6.1. Results: description of the procedure

In order to benefit from the SAEAs approach, a limited number of fitness evaluations is set as stopping criterion; here a value of 400 is used.

The number of samples tested to build the functionability profile (functionability profile calculations per fitness function evaluation) when assessing the fitness functions was 30 in Test Case 1. In Test Case 2, a system with increased complexity and also with greater variability of the outcome of the random distributions that consitute both fitness functions, a value of 1000 was chosen. Therefore, the maximum number of functionability profile calculations allowed in the optimization convergence was 12000 in Test Case 1 and 400000 in Test Case 2.

A multiobjective optimization with NSGA-II, a state-of-the-art multiobjective evolutionary algorithm in cases of two fitness functions, was applied. According to (Deb, 2023) it is one of the most used and cited evolutionary multiobjective algorithms up to date and has been already applied in maintenance optimization as shown in subsection 2.2. Standard parameters were applied: a population size of 100 individuals, SBX crossover with probability of 0.9 and distribution index of 20, polinomial mutation with mutation probability of one divided by the number of variables of the chromosome and distribution index of 20.

Identical configuration was chosen in the SAEA approach, where Kriging surrogates based on four correlation functions were tested: Matern 32, Matern 52, absolute exponential and squared exponential. Therefore, four SAEAs were compared versus the standard NSGA-II algorithm. A set of ten independent executions were taken into account in each case.

In each SAEA execution, in the first iteration, one hundred samples with a maximin Latin Hypercube Sampling were created, which are used to train the Kriging surrogate. It is optimized with NSGA-II using a 100 population and 1000 generations. Then, every generation, a sample of five non-dominated solutions selected with a criterion based on maximum minimum distance in objective space ((Galuzio et al., 2020)) are chosen to be assessed by the fitness function and update the surrogate.

Assesment of the non-dominated set of attained solutions using the hypervolume metric (Emmerich and Deutz, 2018) (the higher the better) and statistical significance tests are shown in next subsections. A reference point of (2,2) was taken into account in the normalized functional space. Scaled factors for the unavailability were 0.003 and 0.00004 for Test Case 1 and 2, respectively. Scaled factors for the cost were 1700 and 4500 economic units for Test Case 1 and 2, respectively.

6.2. Results: test case 1

In Figs. 3 and 4 convergence curves of the mean and median of the hypervolume indicator are shown respectively. Both mean and median show similar behaviour. Curves of the SAEA Kriging Matern32 (green line) first, and SAEA Kriging Matern52 (red line) second, were the best performing ones, and the standard NSGA-II (magenta line) is the worst.

A box plot of the distribution of hypervolume values at the stopping criterion of 400 fitness evaluations is shown in Fig. 5.

These results are supported by a Friedman statistical test of significance, following (Garcia and Herrera, 2008), as shown in Table 2. A p-value of 1.4e-6 (p-value <0.05) confirms the rejection of the null hypothesis H_0 (all algorithms are equal). Results of the Bergmann-Hommel's posthoc procedure are shown in Table 3. They confirm that the two best ordered algorithms in the Friedman test, first the SAEA Kriging Matern32 and second the SAEA Kriging Matern52, outperform both the

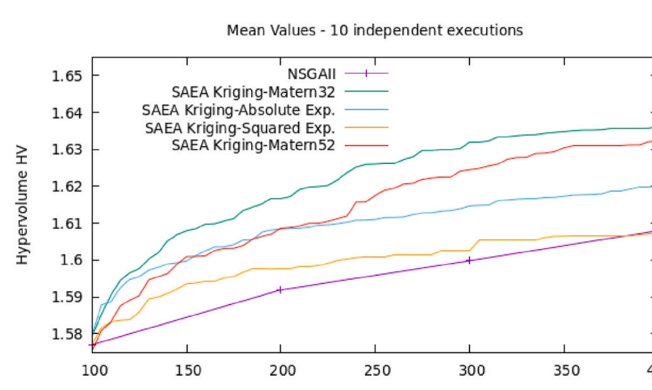

Fig. 3. Hypervolume Convergence, mean values TestCase-1.

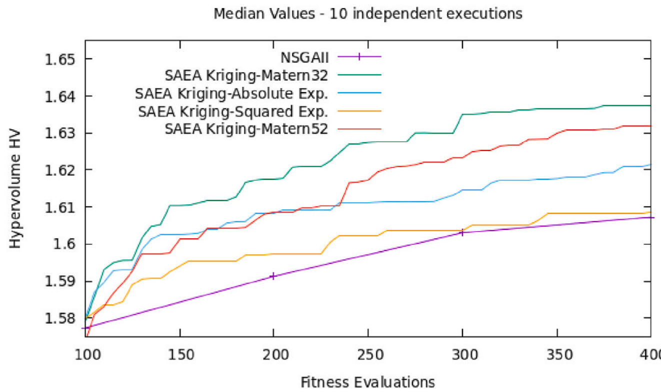

Fig. 4. Hypervolume Convergence, median values TestCase-1.

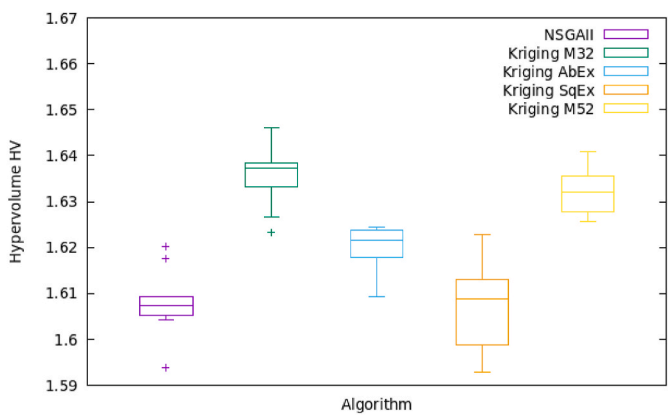

Fig. 5. Boxplot distributions of Hypervolume after 400 fitness evaluations. TestCase-1.

Table 2
Friedman Test. Average rankings of the algorithms based on hypervolume final distribution after 400 fitness function evaluations (the lower the better). TestCase-1.

Algorithm	Ranking
NSGA-II	4.3
Kriging Matern32	1.5
Kriging Absolute Exponential	3.1
Kriging Squared Exponential	4.5
Kriging Matern52	1.6
p-value	1.4e-6

Table 3
Adjusted *p*-values. Bergmann-Hommel's posthoc procedure. TestCase-1.

i	Hypothesis	*p*-value
1	*Krig-Mat32 vs. Krig-SquarExp*	*2.21e-4*
2	*Krig-SquarExp vs. Krig-Mat52*	*2.47e-4*
3	*NSGA-II vs. Krig-Mat32*	*4.50e-4*
4	*NSGA-II vs. Krig-Mat52*	*4.50e-4*
5	Krig-Mat32 vs. Krig-AbsExp	9.46e-2
6	Krig-AbsExp vs. Krig-Mat52	9.46e-2
7	Krig-AbsExp vs. Krig-SquarExp	0.191
8	NSGA-II vs. Krig-AbsExp	0.191
9	NSGA-II vs. Krig-SquarExp	1.55
10	Krig-Mat32 vs. Krig-Mat52	1.55

SAEA Kriging Squared Exponential and the standard NSGA-II algorithm. No other significant differences were detected by the posthoc test.

In Figs. 6 and 7 differences between the best performing algorithm, the SAEA Kriging Matern32, and the NSGA-II were also appreciated when observing their accumulated non-dominated solutions. They were obtained accumulating the non-dominated solutions attained by the final population of each of the ten independent executions of each algorithm. To reduce variability due to the random variable characteristics of the fitness functions, each solution is evaluated here from the average value of 6000 functionability profile calculations (remember that they were built based on the functionability profile construction depending on random variables as shown in Table 1).

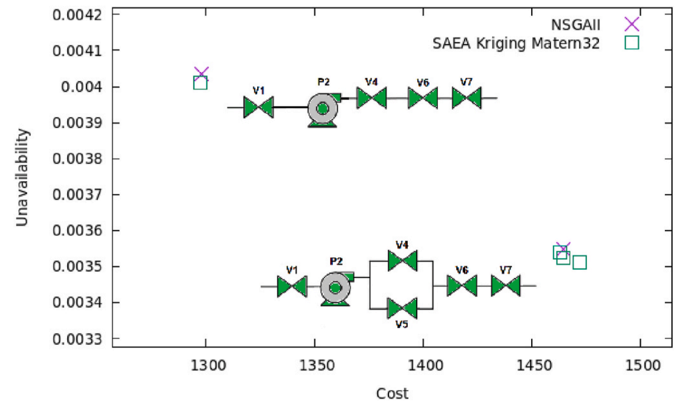

Fig. 6. Non-dominated solutions after 400 fitness evaluations - average samples over 6000 functionability profile calculations. Part a. TestCase-1.

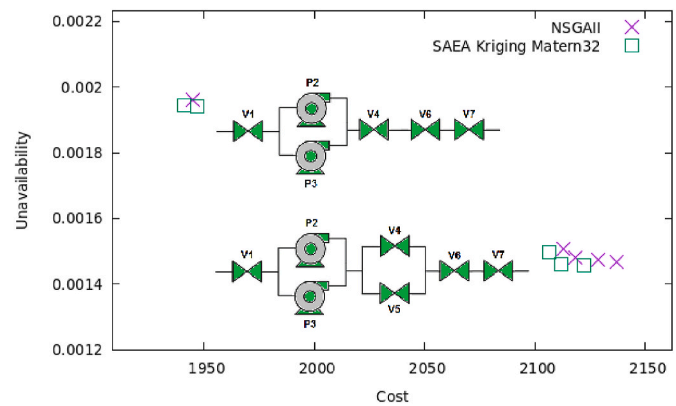

Fig. 7. Non-dominated solutions after 400 fitness evaluations - average samples over 6000 functionability profile calculations. Part b. TestCase-1.

As we are minimizing unavailability and cost, solutions that are more to the left and more at the bottom of the figures are better: squared solutions of the SAEA Kriging Matern 32 versus the crosses solutions of NSGA-II.

The non-dominated front of this first handled test case is not continuous, clearly clustered based on the four device selection layout as in the definition of the test case. Schemes associated to each layout are shown in miniature in each figure. The most expensive components -bombs- imply that when duplicated the system increases its cost and also decreases the unavailability (see Fig. 7). The cheapest cluster is associated with the absence of duplicated components, only a serial line, as shown in the left solutions of Fig. 6.

Optimal maintenance times were integrated in each cluster according to the optimization. The accumulated non-dominated solutions of the SAEA Kriging Matern32 algorithm are detailed in Table 4, including values of cost and unavailability, and maintenance times of each device; if the device is not present in the layout then its maintenance time is shown as 0.

Finally, in Table 5 the hypervolume of the non-dominated solutions computed after average samples over 6000 functionability profile

Table 4
Detailed non-dominated solutions from SAEA Matern32 algorithm, TestCase-1. Times in hours.

F-Cost	F-Unav	Tv1	Tp2	Tp3	Tv4	Tv5	Tv6	Tv7
1297.53	0.004012	22158	0	8760	0	35037	35030	34826
1463.04	0.003539	21625	0	8759	29587	18310	32487	34927
1471.81	0.003513	35038	0	8760	8763	20672	35005	35036
1464.67	0.003524	31332	0	8760	30613	29859	35033	35030
1940.81	0.001946	35018	8746	8760	0	34984	29641	34709
1946.82	0.001940	34992	7819	8757	0	35035	31565	35018
2106.50	0.001498	17192	8634	8690	24907	18791	35002	34983
2111.83	0.001461	35033	7688	8750	28471	31987	34995	30916
2122.18	0.001458	35040	8750	6845	18723	34968	35030	34583

Table 5
Hypervolume of non-dominated solutions computed after average samples over 6000 functionability profile calculations (fpc). TestCase-1. Below the Algorithm type, the number of fpc invested in the optimization process to attain the non-dominated solutions in each case.

Algorithm	Hypervolume
SAEA Kriging Matern32 fpc: 1.2e4	1.581359
NSGA-II fpc: 1.2e4	1.571867
NSGA-II fpc: 1.2e5	1.580728

calculations are shown. The SAEA Kriging Matern32 algorithm not only improves the hypervolume value of NSGA-II with equivalent number of functionability profile calculations (1.2e4), but also it maintains this advantage with an order of magnitude, as the hypervolume of NSGA-II is lower (worse) even at 1.2e5 functionability profile calculations.

6.3. Results: test case 2

In Figs. 8 and 9 convergence curves of the mean and median of the hypervolume indicator are shown respectively. Both mean and median show similar behaviour. Curves of the SAEA Absolute Exponential Kriging (blue line) first, and SAEA Kriging Matern32 (green line) second, are the best performing ones. The SAEA Kriging Squared Exponential (yellow line) and standard NSGA-II (magenta line) are the worst.

A box plot of the distribution of hypervolume values at the stopping criterion of 400 fitness evaluations is shown in Fig. 10.

These results are supported by a Friedman statistical test of significance, as shown in Table 6. A p-value of 7.7e-5 (p-value <0.05) confirms the rejection of the null hypothesis H_0 (all algorithms are equal).

Results of the Bergmann-Hommel's posthoc procedure are shown in Table 7, where those paired comparisons whose p-value is lower than 0.05 are significant. It is confirmed that the best ordered algorithm in

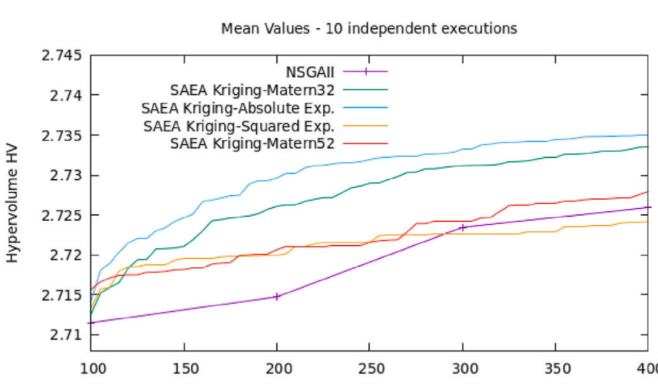

Fig. 8. Hypervolume Convergence, mean values TestCase-2.

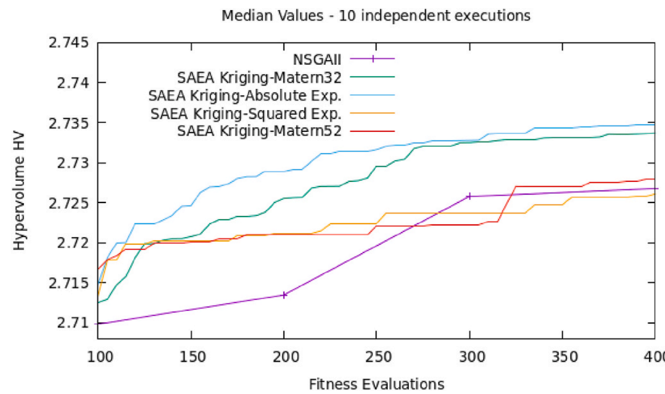

Fig. 9. Hypervolume Convergence, median values TestCase-2.

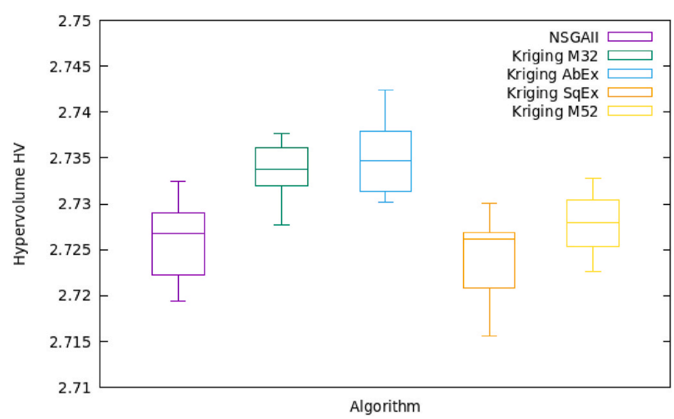

Fig. 10. Boxplot distributions of Hypervolume after 400 fitness evaluations. TestCase-2.

Table 6
Friedman Test. Average rankings of the algorithms based on hypervolume final distribution after 400 fitness function evaluations (the lower the better). TestCase-2.

Algorithm	Ranking
NSGA-II	4.0
Kriging Matern32	2.0
Kriging Absolute Exponential	1.4
Kriging Squared Exponential	4.1
Kriging Matern52	3.5
p-value	7.7e-5

the Friedman test, the SAEA Kriging Absolute Exponential outperforms all the other compared algorithms with the exception of the second ordered algorithm, the SAEA Kriging Matern 32. Also the SAEA Kriging Matern32 is better than the standard NSGA-II and the SAEA Kriging

Table 7
Adjusted *p*-values. Bergmann-Hommel's posthoc procedure. TestCase-2.

i	Hypothesis	*p*-value
1	*Krig-AbsExp vs. Krig-SquarExp*	*1.34e-3*
2	*NSGA-II vs. Krig-AbsExp*	*1.42e-3*
3	*Krig-Mat32 vs. Krig-SquarExp*	*1.79e-2*
4	*Krig-AbsExp vs. Krig-Mat52*	*1.79e-2*
5	*NSGA-II vs. Krig-Mat32*	*1.79e-2*
6	KrigMat32 vs. Krig-Mat52	6.78e-2
7	Krig-SquarExp vs. Krig-Mat52	1.58
8	Krig-Mat32 vs. Krig-AbsExp	1.58
9	NSGA-II vs. Krig-Mat52	1.58
10	NSGA-II vs. Krig-SquarExp	1.58

Squared Exponential. No other significant differences were detected by the posthoc test.

Differences between the best performing algorithm, the SAEA Kriging Absolute Exponential, and the NSGA-II were also appreciated when observing their accumulated non-dominated solutions in Figs. 11 and 12. They were obtained accumulating the non-dominated solutions attained by the final population of each of the ten independent executions of each algorithm. Each solution is evaluated here from the average value of 10000 functionability profile calculations. As we are minimizing unavailability and cost, solutions that are more to the left and more at the bottom of the figures are better: in general, squared solutions of the SAEA Kriging Absolute Exponential versus the crosses solutions of NSGA-II.

Again, the non-dominated front is not continuous. In this Test Case 2, six clusters are identified in the figures with their component devices layouts. Three layouts appear in Fig. 11 containing the optimum designs with higher unavailability and lower cost, all of them without any parallel bomb. Other three layouts appear in Fig. 12 containing the optimum designs with lower unavailability and higher cost, all of them with parallel bombs. A higher variability of designs appear in this work, increasing the type of available systems among optimum designs. In contrast, only the configuration of double serial branches (those most to the left solutions in Fig. 11) appeared in the solutions provided in (Cacereño et al., 2023).

The accumulated non-dominated solutions of the SAEA Kriging Absolute Exponential algorithm are detailed in Table 8, including values of cost and unavailability, and maintenance times of each device; if the device is not present in the layout then its maintenance time is shown as 0.

Finally, in Table 9 the hypervolume of the non-dominated solutions computed after average samples over 10000 functionability profile calculations (fpc) are shown. The SAEA Kriging Absolute Exponential improves the hypervolume value of NSGA-II with equivalent number of functionability profile calculations (4.0e6). In this case it is improved by

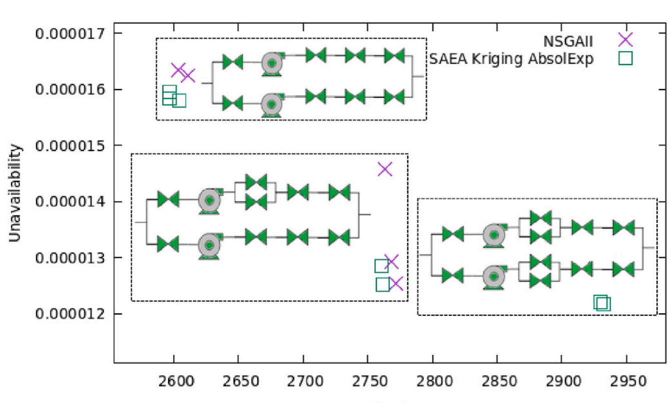

Fig. 11. Non-dominated solutions after 400 fitness evaluations - average samples over 10000 functionability profile calculations. Part a. TestCase-2.

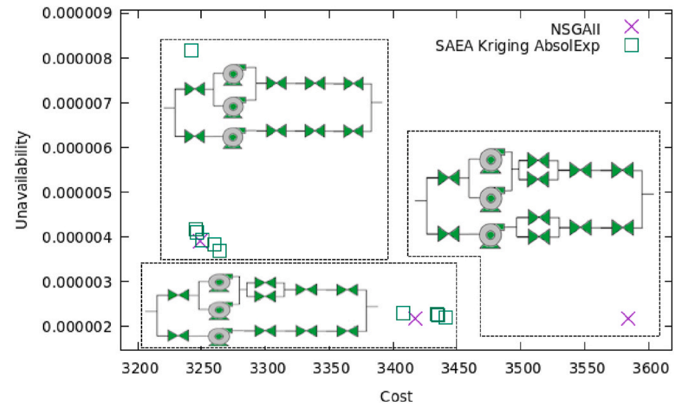

Fig. 12. Non-dominated solutions after 400 fitness evaluations - average samples over 10000 functionability profile calculations. Part b. TestCase-2.

NSGA-II with ten times higher number of fpc (4.0e7). The advantage of SAEAs is greater in Test Case 1 compared with Test Case 2, where the allowed number of evaluations is higher.

6.4. Discussion

Based on the results shown in the previous subsections, four discussion subsections are presented below. First, in relation with the performance of surrogate assisted multiobjective evolutionary algorithms in the maintenance strategy and cost in systems in subsection 6.4.1. Then, in relation with the correlation function in the Kriging surrogate in subsection 6.4.2. Third, in relation with the sampling size when computing the functionability profiles of fitness functions in subsection 6.4.3. And fourth, in relation with several practical implications and potential directions for future work in subsection 6.4.4.

6.4.1. About performance of surrogate assisted multiobjective evolutionary algorithms in the maintenance strategy and cost in systems

The ultimate goal of this research is to increase the efficiency of multi-objective optimization of maintenance strategy with minimum unavailability and minimum maintenance cost for decision making purposes. To contextualize the state of the art prior to this research, several experiments and trials have been carried out in previous publications in pursuit of this goal.

- In (Cacereño et al., 2021), published in 2021, experiments using Test Case 1 as a benchmark and NSGA-II as an optimizer compare different encodings (real, binary and gray), crossover operators (simulated binary crossover SBX, one-point, two-point and uniform crossover), population sizes (50, 100 and 150), parameter configurations (three mutation rates) and chromosome lengths (three values were tested in relation to accuracy levels in scheduling maintenance strategies). Of these, no statistically significant difference in performance was found.
- In (Cacereño et al., 2023), published in 2023, experiments using Test Case 1 as a benchmark compare eight evolutionary multiobjective algorithms. No statistically significant differences were found between the top five algorithms (including NSGA-II).
- In the context of substation automation systems and a simple test case, a multiobjectivization strategy was tested in (Cacereño et al., 2024), published in 2024, comparing the case of two and three objective functions (decomposition of costs into operational cost and adquisition cost). Although the best ordered method of statistical significance test used this multiobjectivization approach, no statistically significant differences were found.

Table 8
Detailed non-dominated solutions from SAEA Absolute Exponential algorithm, TestCase-2. Times in hours.

F-Cost	F-Unav	Tv1	Tp2	Tp3	Tv4	Tv5	Tv6	Tv7	Tv8	Tp9	Tp10	Tv11	Tv12	Tv13	Tv14
2596.45	1.5955E-05	24427	0	8726	0	24963	23473	17091	24225	0	8739	0	20896	34723	27337
2596.51	1.5849E-05	24746	0	8749	0	26738	22192	28402	26639	0	8692	0	30984	19260	31006
2603.84	1.5801E-05	31427	0	8755	0	27437	30325	30125	18688	0	7444	0	19761	20329	25709
2760.66	1.2854E-05	17363	0	8603	35040	32653	30235	22703	27773	0	8633	0	21992	25568	32695
2761.64	1.2522E-05	28724	0	8667	23264	32566	27637	28389	23228	0	8692	0	15099	34985	27848
2929.70	1.2207E-05	35016	0	8735	24158	34755	22781	19671	34687	0	8007	33061	22712	20101	32179
2932.77	1.2168E-05	19563	0	8738	22570	31289	31699	28611	25450	0	8626	9242	27825	33474	35039
3241.92	8.1762E-06	28543	8559	8572	0	16116	23320	25300	22062	0	8256	0	23298	27634	23337
3245.37	4.1808E-06	32749	7998	8760	0	16053	34129	20660	34794	0	8759	0	21260	20069	31022
3246.13	4.0950E-06	32749	7998	8760	0	16053	34129	20660	34794	0	8759	0	21260	20069	31022
3250.76	3.9211E-06	21532	8760	7299	0	35039	33904	35037	35026	0	8756	0	20946	30530	35040
3260.13	3.8216E-06	27924	8759	7754	0	31419	31027	29960	23751	0	6706	0	31928	22805	25265
3263.99	3.6845E-06	27651	6751	7426	0	35040	35039	34988	22865	0	8708	0	27192	23339	21536
3408.27	2.2962E-06	32355	8642	8647	20417	27266	21547	16174	16296	0	8617	0	14004	23786	29815
3434.04	2.2677E-06	28283	6118	8759	24911	12189	23914	20656	34151	0	7931	0	20938	20087	30974
3435.49	2.2504E-06	28283	6118	8759	24911	12189	23914	20656	34151	0	7931	0	20938	20087	30974
3441.60	2.2028E-06	34341	5954	8189	16253	34413	34475	23966	28116	0	7420	0	22374	30856	28863

Table 9
Hypervolume of non-dominated solutions computed after average samples over 10000 functionability profile calculations (fpc). TestCase-2. Below the Algorithm type, the number of fpc invested in the optimization process to attain the non-dominated solutions in each case.

Algorithm	Hypervolume
SAEA Kriging AbsolExp fpc: 4.0e6	2.726773
NSGA-II fpc: 4.0e6	2.723582
NSGA-II fpc: 4.0e7	2.729948

Although this goal has been pursued in the three aforementioned works, no statistically significant differences in performance improvement have been achieved in these previously published studies. On the contrary, in this work, this has been successfully achieved through the proposed methodology: combining multiobjective EAs and surrogate modelling to improve their efficiency. Therefore, in this research work, a way to improve the performance of multi-objective optimization of maintenance strategy with minimum unavailability and minimum maintenance cost for decision-making purposes has been proposed and demonstrated with statistically significant results.

6.4.2. *About the correlation function in Kriging surrogate*

Despite the original MOBOpt algorithm proposes a Matern32 correlation function in the Kriging surrogate, here a study of performance of four correlation functions has been shown. According to the results presented in the two abovementioned subsections 6.2 and 6.3, they evidence the great influence of the correlation function in the SAEAs results.

In both test cases, an unproper choice of the correlation function could lead to results of SAEAs similar to those obtained by the NSGA-II, as was the case of Kriging Squared Exponential in Test Cases 1 and 2. The latter was worse ordered in the Friedman test, but without statistical significance differences in the posthoc test.

The best performing correlation function was not shared by both test cases, being the Kriging Matern32 in Test Case 1 and the Kriging Absolute Exponential in Test Case 2. Nevertheless, Kriging Matern32 has shown a very competitive outcome, being also second ordered by the Friedman test in Test Case 2, and confirmed by posthoc tests better than NSGA-II in both test cases.

This study shows that the choice of the surrogate model used in the optimization plays a critical role in the optimization performance. Therefore, in future studies in real-world scenarios, it is recommended to take into account the type of correlation function in the Kriging surrogate in order to obtain a proper efficiency of the SAMEAs approach. This additional computational effort to compare multiple correlation functions only needs to be done once when the methodology is first implemented and tested in the system of interest, without any additional cost to the operation of the system once the best performing correlation function has been selected.

6.4.3. *About the sampling size when computing functionability profiles of fitness functions*

In this manuscript we assess the fitness functions of unavailability and cost relying in the discrete simulation of the functionability profile, which constitute random variables. Therefore the size of the sample used in their evaluations conditions the variability of the outcome. As representative example, in Fig. 13 unavailability and cost of one random solution of Test Case 2 is evaluated with two sampling sizes of 30 (magenta crosses) and 1000 (green xs). Thirty evaluations were shown.

As observed, the higher the sampling size, the lower the uncertainty in the prediction of the unavailability and cost of the system, but also the higher the computational cost of the assesment.

Therefore, having an adequate optimization methodology that contributes to require a smaller number of evaluations is important. According to the results presented in this manuscript, the SAEAs approach could contribute in this direction, allowing to reduce the number of fitness functions when using more costly (with higher number of samples) predictions.

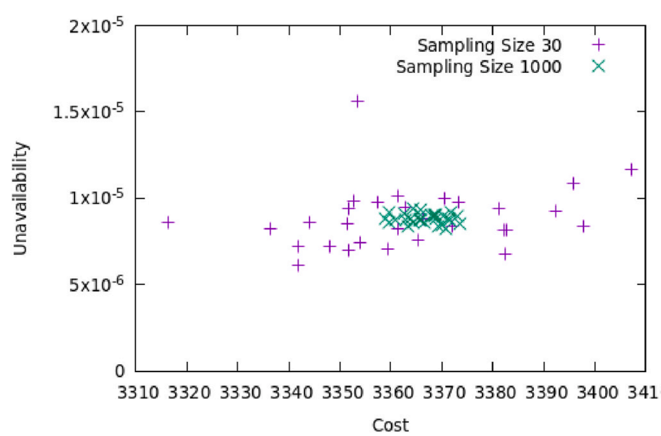

Fig. 13. Example of evaluation of fitness functions as average of N samples of functionability profile calculations: sampling sizes of N = 30 and N = 1000. TestCase-2.

6.4.4. Further practical implications and future work

SAEAs for multi-objective reliability optimization improve the methodology/tool for designing an optimal maintenance policy: Support the design of maintenance strategies that jointly provide the correct system equipment/devices for the lower maintenance system cost (also based on optimal maintenance times for each component) given for each system unavailability rate; or, alternatively, the lower system unavailability rate given for each maintenance system cost. With the obtained non-dominated solutions, the maintenance strategy decision makers have a tool capable of automatically providing the system equipment configuration and its maintenance calendar times that are optimal from the point of view of minimum system unavailability, given a given maintenance cost.

This methodology could also promote the benefits of optimized preventive maintenance when hybridised with other types of maintenance, as shown in (Bilal Yıldız and Soylu, 2023), which presents a recent novel approach that integrates preventive and predictive maintenance policies using system dynamics and a decision table using traditional and machine learning methods. It allows for the possibility of ignoring some maintenance actions depending on the circumstances and demonstrates the usefulness of its approach in several scenarios. As a result, this strategy helps to rationally allocate limited resources to maintenance actions. Another hybrid maintenance strategy is proposed in (Liu et al., 2024). They propose a condition-based maintenance policy that integrates hybrid preventive maintenance and periodic inspections for leased equipment. This policy, which integrates imperfect preventive maintenance, preventive replacement and corrective maintenance, allows the lessor to decide on maintenance actions based on the condition of the equipment. The hybrid policy can reduce costs for the lessor compared to a single preventive maintenance strategy.

As future work, we propose the design of maintenance strategies that perform a surrogate-assisted multi-objective optimization, as successfully demonstrated in this work, directly considering random distributions of equipment maintenance times (as shown in Table 1) based on the RUL estimate. This estimation, if characteristic data of the physical device are available (as in the case of DT), could be performed using AI/machine learning techniques (e.g. as in (Zhong et al., 2023) using a long short-term convolutional neural network LSTM-CNN) which is also not a deterministic but a stochastic estimation. Therefore, it could be included as a random variable in the construction of the functionability profile of the system and evaluated as explained in section 4.2. This would be a challenge much closer to the operability of predictive maintenance systems in DT (Bechina and Arntzen, 2022) (Marzouk and Zaher, 2020) (Shaheen and Németh, 2022).

Kriging methods have certain limitations in terms of the number of variables that can be handled efficiently in the surrogate model. Therefore, this could be a limitation in the number of devices integrated in the optimized system. One research to be explored to overcome this limitation would be the use of Kriging modelling methods for high-dimensional problems (e.g. (Zhao et al., 2019):), or the use of metamodels based on machine learning techniques (deep learning (LeCun et al., 2015), XGBoost (Chen and Guestrin, 2016)). Nevertheless, high-dimensional expensive optimization problems, and especially high-dimensional expensive multiobjective optimization problems, remain as one of the most challenging problems in the field (as stated e.g., in (He et al., 2023)).

7. Conclusions

In this research, the use of multiobjective surrogate-assisted evolutionary algorithms (SAEAs) has enhanced the development of efficient strategies to plan maintenance activities of systems, improving simultaneously their unavailability and cost. The set of achieved non-dominated designs provide assignment of times for preventive maintenance activities combined with the assignment of devices/components of the system layout.

Experimental results in two containment spray injection system models prove the better performance of multiobjective SAEAs compared with the state of the art NSGA-II confirmed by statistical significance tests. SAEAs were capable of obtaining better solutions when compared in terms of equal number of fitness evaluations, or alternatively, being capable of obtaining similar quality of solutions in terms of the hypervolume indicator in less orders of magnitude in terms of the required number of fitness evaluations.

DTs could benefit from this methodology in order to accurately simulate and plan for decision-making purposes, coupling with reliability and failure data of the physical system, including the maintenance to ensure continuity of operation of the physical entity.

Contributions

All authors contributed to the study conception and design. Software was implemented by DG and AC. Analysis of results was performed by all authors. The first draft of the manuscript was written by DG. All authors reviewed and approved the final manuscript.

Appendix

Definitions of the system parameters shown in Table 1 required to build the functionability profile of the system (Cacereño et al., 2023).

- Life Cycle = The system mission time (expressed in hours).
- Corrective Maintenance Cost = The cost entailed in developing a repair activity to recover the system following a failure (expressed in economic units per hour).
- Preventive Maintenance Cost = The cost entailed in developing a preventive maintenance activity (expressed in relation to the Corrective Maintenance Cost).
- Pump TF_{min} = The minimum operation Time To Failure for a pump without preventive maintenance (expressed in hours). It is considered that a failure of a pump can not occur before this time.
- Pump TF_{max} = The maximum operation Time To Failure for a pump without preventive maintenance (expressed in hours). It is mandatory that the failure of a pump occurs before this time.
- Pump TF λ = The failure rate for a pump, which follows an exponential failure distribution (expressed in hours raised to the power of minus six).
- Pump TR_{min} = The minimum Time To Repair or duration of a corrective maintenance activity for a pump (expressed in hours).
- Pump TR_{max} = The maximum Time To Repair or duration of a corrective maintenance activity for a pump (expressed in hours).
- Pump TR μ = The mean for the normal distribution followed for the Time To Repair assumed for a pump (expressed in hours).
- Pump TR σ = The standard deviation for the normal distribution followed for the Time To Repair assumed for a pump (expressed in hours).
- Pump TP_{min} = The minimum operation Time To Start following a scheduled Preventive Maintenance activity for a pump (expressed in hours). It is considered that a Preventive Maintenance activity for a pump is not necessary before this time.
- Pump TP_{max} = The maximum operation Time To Start following a scheduled Preventive Maintenance activity for a pump (expressed in hours). It is considered that a Preventive Maintenance activity for a pump is a recklessness after this time. It should be done before this time.
- Pump TRP_{min} = The minimum Time To Perform a preventive maintenance activity for a pump (expressed in hours). It is the minimum time needed to develop the Preventive Maintenance activity for a pump.
- Pump TRP_{max} = The maximum Time To Perform a preventive maintenance activity for a pump (expressed in hours). It is the

maximum time needed to develop the Preventive Maintenance activity for a pump.

- Valve TF_{min} = The minimum operation Time To Failure for a valve without preventive maintenance (expressed in hours). It is considered that a failure of a valve can not occur before this time.
- Valve TF_{max} = The maximum operation operation Time To Failure for a valve without preventive maintenance (expressed in hours). It is mandatory that the failure of a valve occurs before this time.
- Valve TF λ = The failure rate for a valve, which follows an exponential failure distribution (expressed in hours raised to the power of minus six).
- Valve TR_{min} = The minimum Time To Repair or duration of a corrective maintenance activity for a valve (expressed in hours).
- Valve TR_{max} = The maximum Time To Repair or duration of a corrective maintenance activity for a valve (expressed in hours).
- Valve TR μ = The mean for the normal distribution followed for the Time To Repair assumed for a valve (expressed in hours).
- Valve TR σ = The standard deviation for the normal distribution followed for the Time To Repair assumed for a valve (expressed in hours).
- Valve TP_{min} = The minimum operation Time To Start following a scheduled Preventive Maintenance activity for a valve (expressed in hours). It is considered that a Preventive Maintenance activity for a valve is not necessary before this time.
- Valve TP_{max} = The maximum operation Time To Start following a scheduled Preventive Maintenance activity for a valve (expressed in hours). It is considered that a Preventive Maintenance activity for a valve is a recklessness after this time. It should be done before this time.
- Valve TRP_{min} = The minimum Time To Perform a preventive maintenance activity for a valve (expressed in hours). It is the minimum time needed to develop the Preventive Maintenance activity for a valve.
- Valve TRP_{max} = The maximum Time To Perform a preventive maintenance activity for a valve (expressed in hours). It is the maximum time needed to develop the Preventive Maintenance activity for a valve.

CRediT authorship contribution statement

David Greiner: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **Andrés Cacereño:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

Andrews, J., Moss, T., 2002. Reliability and Risk Assessment, second ed. The American Society of Mechanical Engineers.

Arisekola, K., Madson, K., 2023. Digital twins for asset management: Social network analysis-based review. Autom. ConStruct. 150, 104833 https://doi.org/10.1016/j.autcon.2023.104833.

Attaran, S., Attaran, M., Celik, B.G., 2024. Digital twins and industrial internet of things: Uncovering operational intelligence in industry 4.0, Decision Analytics. Journal 10, 100398. https://doi.org/10.1016/j.dajour.2024.100398.

Bäck, T.H.W., Kononova, A.V., van Stein, B., Wang, H., Antonov, K.A., Kalkreuth, R.T., de Nobel, J., Vermetten, D., de Winter, R., Ye, F., 2023. Evolutionary algorithms for parameter optimization—thirty years later. Evol. Comput. 31 (2), 81–122. https://doi.org/10.1162/evco_a_00325.

Badenko, V., Bolshakov, N., Tishchenko, E., Fedotov, A., Celani, A., Yadykin, V., 2021. Integration of digital twin and BIM technologies within factories of the future. Magazine of Civil Engineering. https://doi.org/10.34910/MCE.101.14.

Bechina, K., Arntzen, A., 2022. A system of systems approach to smart building management: an AI vision for facility management. In: 17th Annual System of Systems Engineering Conference (SOSE). IEEE.

Bilal Yıldız, G., Soylu, B., 2023. Integrating preventive and predictive maintenance policies with system dynamics: a decision table approach. Adv. Eng. Inf. 56, 101952 https://doi.org/10.1016/j.aei.2023.101952.

Bouhlel, M.A., Hwang, J.T., Bartoli, N., Lafage, R., Morlier, J., Martins, J.R., 2019. A python surrogate modeling framework with derivatives. Adv. Eng. Software 135, 102662. https://doi.org/10.1016/j.advengsoft.2019.03.005.

Briš, R., Tran, N.T.T., 2023. Discrete model for a multi-objective maintenance optimization problem of safety systems. Mathematics 11 (2), 320. https://doi.org/10.3390/math11020320.

Cacereño, A., Greiner, D., Galván, B.J., 2021. Multi-objective optimum design and maintenance of safety systems: an in-depth comparison study including encoding and scheduling aspects with NSGA-II. Mathematics 9 (15), 1751. https://doi.org/10.3390/math9151751.

Cacereño, A., Greiner, D., Galván, B., 2023. Simultaneous optimization of design and maintenance for systems using multi-objective evolutionary algorithms and discrete simulation. Soft Comput. 27 (24), 19213–19246. https://doi.org/10.1007/s00500-023-08922-2.

Cacereño, A., Greiner, D., Zuñiga, A., Galván, B.J., 2024. Design and maintenance optimisation of substation automation systems: a multiobjectivisation approach exploration. J. Eng. 2024, 1–19. https://doi.org/10.1155/2024/9390545.

Chen, T., Guestrin, C., 2016. XGBoost: a scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM.

Chen, C., Fu, H., Zheng, Y., Tao, F., Liu, Y., 2023. The advance of digital twin for predictive maintenance: the role and function of machine learning. J. Manuf. Syst. 71, 581–594. https://doi.org/10.1016/j.jmsy.2023.10.010.

Cheng, D., Lu, Z., Zhou, J., Liang, X., 2023. An optimizing maintenance policy for airborne redundant systems operating with faults by using markov process and NSGA-II. Reliab. Eng. Syst. Saf. 236, 109257 https://doi.org/10.1016/j.ress.2023.109257.

Cimino, C., Ferretti, G., Leva, A., 2021. Harmonising and integrating the digital twins multiverse: a paradigm and a toolset proposal. Comput. Ind. 132, 103501 https://doi.org/10.1016/j.compind.2021.103501.

Cui, Z., Yang, X., Yue, J., Liu, X., Tao, W., Xia, Q., Wu, C., 2023. A review of digital twin technology for electromechanical products: Evolution focus throughout key lifecycle phases. J. Manuf. Syst. 70, 264–287. https://doi.org/10.1016/j.jmsy.2023.07.016.

Dahiya, D., Laishram, B., 2024. Life cycle energy analysis of buildings: a systematic review. Build. Environ. 111160doi. https://doi.org/10.1016/j.buildenv.2024.111160.

Deb, K., 2023. An interview with Kalyanmoy Deb 2022 ACM fellow. SIGEVOlution 16 (1), 1–6. https://doi.org/10.1145/3594261.3594262.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6 (2), 182–197. https://doi.org/10.1109/4235.996017.

Deng, S., Ling, L., Zhang, C., Li, C., Zeng, T., Zhang, K., Guo, G., 2023. A systematic review on the current research of digital twin in automotive application. Internet of Things and Cyber-Physical Systems 3, 180–191. https://doi.org/10.1016/j.iotcps.2023.04.004.

D'Amico, R.D., Erkoyuncu, J.A., Addepalli, S., Penver, S., 2022. Cognitive digital twin: an approach to improve the maintenance management. CIRP Journal of Manufacturing Science and Technology 38, 613–630. https://doi.org/10.1016/j.cirpj.2022.06.004.

Emmerich, M.T.M., Deutz, A.H., 2018. A tutorial on multiobjective optimization: fundamentals and evolutionary methods. Nat. Comput. 17 (3), 585–609. https://doi.org/10.1007/s11047-018-9685-y.

Emmerich, M., Giannakoglou, K., Naujoks, B., 2006. Single- and multiobjective evolutionary optimization assisted by Gaussian random field metamodels. IEEE Trans. Evol. Comput. 10 (4), 421–439. https://doi.org/10.1109/tevc.2005.859463.
Errandonea, I., Beltrán, S., Arrizabalaga, S., 2020. Digital twin for maintenance: a literature review. Comput. Ind. 123, 103316 https://doi.org/10.1016/j.compind.2020.103316.
Galuzio, P.P., de Vasconcelos Segundo, E.H., dos Santos Coelho, L., Mariani, V.C., 2020. MOBOpt — multi-objective bayesian optimization. SoftwareX 12, 100520. https://doi.org/10.1016/j.softx.2020.100520.
Garcia, S., Herrera, F., 2008. An extension on 'statistical comparisons of classifiers over multiple data sets'' for all pairwise comparisons. J. Mach. Learn. Res. 9, 2677–2694.
Genton, M., 2001. Classes of kernels for machine learning: a statistics perspective. J. Mach. Learn. Res. 2, 299–312.
Greiner, D., Galván, B., Winter, G., 2003. Safety systems optimum design by multicriteria evolutionary algorithms. In: Lecture Notes in Computer Science. Springer, Berlin Heidelberg, pp. 722–736. https://doi.org/10.1007/3-540-36970-8_51.
Greiner, D., Periaux, J., Emperador, J.M., Galván, B., Winter, G., 2017. Game theory based evolutionary algorithms: a review with Nash applications in structural engineering optimization problems. Arch. Comput. Methods Eng. 24 (4), 703–750. https://doi.org/10.1007/s11831-016-9187-y.
Guo, J., Yang, Z., Chen, C., Luo, W., Hu, W., 2021. Real-time prediction of remaining useful life and preventive maintenance strategy based on digital twin. J. Comput. Inf. Sci. Eng. 21 (3) https://doi.org/10.1115/1.4049153.
Haftka, R.T., Villanueva, D., Chaudhuri, A., 2016. Parallel surrogate-assisted global optimization with expensive functions – a survey. Struct. Multidiscip. Optim. 54 (1), 3–13. https://doi.org/10.1007/s00158-016-1432-3.
He, C., Zhang, Y., Gong, D., Ji, X., 2023. A review of surrogate-assisted evolutionary algorithms for expensive optimization problems. Expert Syst. Appl. 217, 119495 https://doi.org/10.1016/j.eswa.2022.119495.
Jin, Y., 2003. A comprehensive survey of fitness approximation in evolutionary computation. Soft Comput. 9 (1), 3–12. https://doi.org/10.1007/s00500-003-0328-5.
Jin, Y., 2011. Surrogate-assisted evolutionary computation: recent advances and future challenges. Swarm Evol. Comput. 1 (2), 61–70. https://doi.org/10.1016/j.swevo.2011.05.001.
Jin, Y., Sendhoff, B., 2002. Fitness approximation in evolutionary computation - a survey. In: Proceedings of Genetic and Evolutionary Computation Conference. ACM, pp. 1105–1112.
Jin, Y., Wang, H., Chugh, T., Guo, D., Miettinen, K., 2019. Data-driven evolutionary optimization: an overview and case studies. IEEE Trans. Evol. Comput. 23 (3), 442–458. https://doi.org/10.1109/tevc.2018.2869001.
Jin, Y., Wang, H., Sun, C., 2021. Data-Driven Evolutionary Optimization. Springer International Publishing. https://doi.org/10.1007/978-3-030-74640-7.
Jones, D.R., Schonlau, M., Welch, W.J., 1998. Efficient global optimization of expensive black-box functions. J. Global Optim. 13 (4), 455–492. https://doi.org/10.1023/a:1008306431147.
Knowles, J., 2006. ParEGO: a hybrid algorithm with on-line landscape approximation for expensive multiobjective optimization problems. IEEE Trans. Evol. Comput. 10 (1), 50–66. https://doi.org/10.1109/tevc.2005.851274.
LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521 (7553), 436–444. https://doi.org/10.1038/nature14539.
Levitin, G., Lisnianski, A., 1999. Joint redundancy and maintenance optimization for multistate series–parallel systems. Reliab. Eng. Syst. Saf. 64 (1), 33–42. https://doi.org/10.1016/s0951-8320(98)00052-0.
Liu, B., Pang, J., Yang, H., Zhao, Y., 2024. Optimal condition-based maintenance policy for leased equipment considering hybrid preventive maintenance and periodic inspection. Reliab. Eng. Syst. Saf. 242, 109724 https://doi.org/10.1016/j.ress.2023.109724.
Madubuike, O.C., Anumba, C.J., 2023. Digital twin–based health care facilities management. J. Comput. Civ. Eng. 37 (2) https://doi.org/10.1061/jccee5.cpeng-4842.
Maneckshaw, B., Mahapatra, G.S., 2022. Multi-objective evolutionary algorithm on reliability redundancy allocation with interval alternatives for system parameters. Neural Comput. Appl. 34 (21), 18595–18609. https://doi.org/10.1007/s00521-022-07459-z.
Marzouk, M., Zaher, M., 2020. Artificial intelligence exploitation in facility management using deep learning. Construct. Innovat. 20 (4), 609–624. https://doi.org/10.1108/ci-12-2019-0138.
Matsuo, Y., Shimogori, A., Suzuki, A., 2015. Major issues regarding nuclear power generation costs assessment in Japan. IEEJ Energy J 10 (2), 47–90.
Mergos, P.E., 2022. Surrogate-based optimum design of 3d reinforced concrete building frames to eurocodes. Developments in the Built Environment 11, 100079. https://doi.org/10.1016/j.dibe.2022.100079.
Nourelfath, M., Châtelet, E., Nahas, N., 2012. Joint redundancy and imperfect preventive maintenance optimization for series–parallel multi-state degraded systems. Reliab. Eng. Syst. Saf. 103, 51–60. https://doi.org/10.1016/j.ress.2012.03.004.
OREDA, 2009. OREDA – Offshore Reliability Data Handbook, fifth ed. Det Norske Veritas (DNV). OREDA participants, Prepared by: SINTEF, Distributed by.
Osaba, E., Villar-Rodriguez, E., Ser, J.D., Nebro, A.J., Molina, D., LaTorre, A., Suganthan, P.N., Coello, C.A.C., Herrera, F., 2021. A tutorial on the design, experimentation and application of metaheuristic algorithms to real-world optimization problems. Swarm Evol. Comput. 64, 100888 https://doi.org/10.1016/j.swevo.2021.100888.
Pita, O., 2019. Introduction to aircraft maintenance programs. In: COSCAP SEA-EASA Air Meeting. European Union Aviation Safety Agency.
Priyangga, H., Ruliandi, D., 2018. Application of pattern recognition and classification using artificial neural network in geothermal operation. In: Proceedings, 43rd Workshop on Geothermal Reservoir Engineering.
Rahman, M.A., Taheri, H., Dababneh, F., Karganroudi, S.S., Arhamnamazi, S., 2024. A review of distributed acoustic sensing applications for railroad condition monitoring. Mech. Syst. Signal Process. 208, 110983 https://doi.org/10.1016/j.ymssp.2023.110983.
Ruliandi, D., 2015. Geothermal power plant system performance prediction using artificial neural networks. In: 2015 IEEE Conference on Technologies for Sustainability (SusTech). IEEE. https://doi.org/10.1109/sustech.2015.7314349.
Sacks, J., Schiller, S.B., Welch, W.J., 1989. Designs for computer experiments. Technometrics 31 (1), 41–47. https://doi.org/10.1080/00401706.1989.10488474.
Saves, P., Lafage, R., Bartoli, N., Diouane, Y., Bussemaker, J.H., Lefebvre, T., Hwang, J. T., Morlier, J., Martins, J.R.R.A., 2023. Smt 2.0: a surrogate modeling toolbox with a focus on hierarchical and mixed variables Gaussian processes. ArXiv preprint. https://doi.org/10.48550/arXiv.2305.13998.
Shaheen, B.W., Németh, I., 2022. Integration of maintenance management system functions with industry 4.0 technologies and features—a review. Processes 10 (11), 2173. https://doi.org/10.3390/pr10112173.
Soori, M., Arezoo, B., Dastres, R., 2024. Virtual manufacturing in industry 4.0: a review. Data Science and Management 7 (1), 47–63. https://doi.org/10.1016/j.dsm.2023.10.006.
Stork, J., Friese, M., Zaefferer, M., Bartz-Beielstein, T., Fischbach, A., Breiderhoff, B., Naujoks, B., Tusar, T., 2019. Open issues in surrogate-assisted optimization. In: High-Performance Simulation-Based Optimization. Springer International Publishing, pp. 225–244. https://doi.org/10.1007/978-3-030-18764-4_10.
Sun, Z., Xing, J., Tang, P., Cooke, N.J., Boring, R.L., 2020. Human reliability for safe and efficient civil infrastructure operation and maintenance – a review. Developments in the Built Environment 4, 100028. https://doi.org/10.1016/j.dibe.2020.100028.
van Dinter, R., Tekinerdogan, B., Catal, C., 2022. Predictive maintenance using digital twins: a systematic literature review. Inf. Software Technol. 151, 107008 https://doi.org/10.1016/j.infsof.2022.107008.
Venkatesan, S., Manickavasagam, K., Tengenkai, N., Vijayalakshmi, N., 2019. Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin. IET Electr. Power Appl. 13 (9), 1328–1335. https://doi.org/10.1049/iet-epa.2018.5732.
Wan, J., Tang, S., Li, D., Wang, S., Liu, C., Abbas, H., Vasilakos, A.V., 2017. A manufacturing big data solution for active preventive maintenance. IEEE Trans. Ind. Inf. 13 (4), 2039–2047. https://doi.org/10.1109/tii.2017.2670505.
Wayan Ngarayana, I., Do, T.-M.-D., Murakami, K., Suzuki, M., 2019. Nuclear power plant maintenance optimisation: models, methods and strategies. J. Phys. Conf. 1198 (2), 022005 https://doi.org/10.1088/1742-6596/1198/2/022005.
Xia, J., Zou, G., 2023. Operation and maintenance optimization of offshore wind farms based on digital twin: a review. Ocean Engineering 268, 113322. https://doi.org/10.1016/j.oceaneng.2022.113322.
Zaparoli Cunha, B., Droz, C., Zine, A.-M., Foulard, S., Ichchou, M., 2023. A review of machine learning methods applied to structural dynamics and vibroacoustic. Mech. Syst. Signal Process. 200, 110535 https://doi.org/10.1016/j.ymssp.2023.110535.
Zhang, Q., Liu, W., Tsang, E., Virginas, B., 2010. Expensive multiobjective optimization by MOEA/d with Gaussian process model. IEEE Trans. Evol. Comput. 14 (3), 456–474. https://doi.org/10.1109/tevc.2009.2033671.
Zhao, L., Wang, P., Song, B., Wang, X., Dong, H., 2019. An efficient kriging modeling method for high-dimensional design problems based on maximal information coefficient. Struct. Multidiscip. Optim. 61 (1), 39–57. https://doi.org/10.1007/s00158-019-02342-3.
Zhao, J., Feng, X., Pang, Q., Fowler, M., Lian, Y., Ouyang, M., Burke, A.F., 2024. Battery safety: machine learning-based prognostics. Prog. Energy Combust. Sci. 102, 101142 https://doi.org/10.1016/j.pecs.2023.101142.
Zhong, D., Xia, Z., Zhu, Y., Duan, J., 2023. Overview of predictive maintenance based on digital twin technology. Heliyon 9 (4), e14534. https://doi.org/10.1016/j.heliyon.2023.e14534.