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Research Article

Design and Maintenance Optimisation of Substation Automation Systems: A Multiobjectivisation Approach Exploration

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Substation automation systems (SAS) are critical infrastructures whose design and maintenance must be optimised to guarantee a suitable performance. In order to provide a collection of solutions that balance availability and cost, this paper explores the optimisation of the design and maintenance of a section of SAS. Multiobjective evolutionary algorithms are combined with discrete event simulation while the performance of two state-of-the-art multiobjective evolutionary algorithms is studied. On the one hand, the nondominated sorting genetic algorithm II (NSGA-II), and on the other hand, the S-metric selection evolutionary multiobjective optimisation algorithm (SMS-EMOA). Such a problem is solved from 2 and 3-objective approaches by attending to the multiobjectivisation concept. The robustness of the methodology is brought to light, and benefits were observed from the multiobjectivisation approach. Decision-makers can employ this knowledge to make informed decisions based on economic and reliability criteria.

1. Introduction

The greater the technological improvement, the greater the energy demand from modern societies. In order to meet this demand, power systems must face several challenges. Numerous standards are employed to integrate substation gadgets, which are provided by several manufacturers, enabling peer-to-peer communications among such gadgets [1]. Standards are a research topic due to the fact that the designers of systems must propose the architectural design. They must decide on the design according to the criticality of the applications [2].

Reliability and maintenance data are needed to evaluate the reliability, communication, and design of SAS [3]. According to the design, the reliability of SAS has been widely studied by employing reliability block diagrams [4–7], fault tree analysis [8], Monte Carlo simulation [2], and Markov chain analysis [1]. Using discrete event simulation allows a closer approximation to reality when the behaviour of the system must be emulated. It is possible through building the system's functionality profile. It allows the use of nonconstant failure and repair rates. Instead of reliability, the term availability should be used to refer to repairable systems. Availability encompasses the whole process of failure and recovery. Therefore, maintenance is also considered when the term availability is used. Several studies contemplated corrective maintenance of SAS [1, 2, 4, 5], but, none of them took preventive maintenance into account. Preventive maintenance improves the SAS availability; nevertheless, it was not considered by many studies. Diaz et al. [9] conducted a study where a model to quantify the profit-cost of a process bus solution was developed. They considered preventive maintenance activities by fixing a period based on either business experience or historical data. Nevertheless, there are no contributions focused on the simultaneous optimisation of SAS design and maintenance.

Multiobjective optimisation has been widely employed to manage complex engineering problems with conflicting objectives. Finding out the best solution for such problems is a difficult task, since there are a large number of feasible solutions. Nevertheless, some good solutions can be found to meet the engineers' requirements [10, 11]. Several authors have considered the possibility of using multiobjective algorithms that rely exclusively on genotypic values to enhance the performance of single-objective optimisation problems [12]. The term multiobjectivisation has been used in order to refer to such a technique. Although its principles had already been discussed by Louis and Rawlins [13], Knowles et al. first employed the term multiobjectivisation [14]. Two multiobjectivisation approaches were distinguished by the authors: decomposition, which consists of breaking down the main objective into a number of objectives, and aggregation, which consists of taking into account some additional objectives (helper objectives) to combine them with the main objective. Complex optimisation problems have been solved employing multiobjectivisation [15–18]. Some performance advantages have been reported. Nevertheless, employing multiobjectivisation to solve multiobjective problems has not received as much attention. In Ishibuchi et al. [19], a 2-objective problem is solved after converting it into a four-objective problem. They used a decomposition approach. On the other hand, in Zheng et al. [20], in order to foster intertask understanding transfer in a multitask optimisation problem, a helper task is employed by using an aggregation approach.

SAS designers want optimum performance, so maximising the system availability is vital in order to meet the demand from customers. In the present research, based on work belonging to the doctoral thesis of the first author [21], Multiobjective evolutionary algorithms and discrete event simulation are combined. The main target consists in optimising both the design and the maintenance strategy for SAS. Such a procedure was previously studied by some of the authors of this research [22–24]. Such studies considered hydraulic systems whose design and maintenance strategy were optimised by using Unavailability and operational cost as objective functions. In the present study, a decomposition approach is explored to assess the performance when studying two and three objectives. To solve the 2-objective problem, the objectives to be managed are unavailability and cost. Both the acquisition and operational costs are considered by the cost model. The cost model is decomposed between the acquisition cost and the operational cost when considering the multiobjectivisation approach. Hence, the objectives in the 3-objective problem are unavailability, acquisition cost, and operational cost. To summarise the contributions of the study:

(i) The present paper explores a methodology, which is considered a powerful tool to assist SAS designers in the sensitive process of simultaneously proposing the architectonic design and the maintenance policy for SAS. The architectonic design consists of the automatic selection of gadgets while the preventive maintenance policy consists of establishing the optimum times to initiate the preventive maintenance activities regarding the gadgets included in such a design. The simultaneous optimisation of the design and maintenance of SAS has not been tackled before. It allows a more efficient system life cycle because maintenance activities are fully optimised and customised to the architectonic design.

(ii) Multiobjective evolutionary algorithms are combined with discrete event simulation. When the behaviour of the system wants to be emulated by building its functionability profile, discrete event simulation allows a closer approximation to reality than other methods used in the literature. Previously, such a methodology was analysed by some authors of the present research as explained above. Unavailability and operational cost were taken into account as objectives of the multiobjective problem. However, in this case, the cost model is renewed in order to consider both the acquisition and the operational cost.

(iii) A comparative study is developed to study the impact of multiobjectivisation. Such an approach has never been applied in the field of system reliability. First, the 2-objective problem is solved by attending to unavailability and cost (including both operational and acquisition costs) as objectives. Second, the 3-objective problem is addressed by considering a multiobjectivisation approach. In this case, acquisition and operational costs are taken from the cost model previously used. Hence, the problem to solve presents three objectives: unavailability, operational cost, and acquisition cost. Finally, a comparative analysis of the performance under both approaches is supplied. The multiobjectivisation approach presents some advantage.

In this paper, Section 2 summarises the methodology. A case study is presented in Section 3. Section 4 shows and discusses the results, and finally, the conclusions are displayed in Section 5.

2. Materials and Methods

This paper explores the simultaneous optimisation of the design and maintenance of SAS in relation to the availability and cost objective functions, which are extensively described in Subsection 2.1. To compute these objectives, it is necessary to build the functionability profile of the system, which emulates its behaviour over time. This is explained in Subsection 2.2. From the multiobjective optimisation point of view, the multiobjectivisation technique is explored, as described in Subsection 2.3. These mathematical models and the procedures are shown below, while the methodology is applied to a case study (as described in Section 3).

2.1. Availability and Costs Models. The availability of a gadget can be computed by using equation (1) when its failure and repair rates are constant. In this case, the mean time to failure (MTTF) and the mean time to repair (MTTR) are considered as operation and recovery time, respectively [25]. Therefore, the model exclusively reflects corrective maintenance.

$$A = \frac{\text{MTTF}}{\text{MTTF} + \text{MTTR}}. \quad (1)$$

When such rates are not constant, computing the availability of the gadget can be a difficult task. In this case, it is useful to consider a simulation approach. Such an approach is used in this study to compute the system availability. Instead of using the MTTF, each time to failure (TF) is randomly produced from the density function that represents the times to failure. Furthermore, each time to repair (TR) is randomly generated from the density function that characterises the times to repair. In this way, the corrective maintenance is considered by the model. Apart from that, in order to consider preventive maintenance, the operation time must contemplate both times of failure and times to initiate a preventive maintenance activity (TM). Furthermore, the recovery time must consider both times to repair and times to carry out a preventive maintenance activity (TCM). Taking these considerations, the model to compute the system availability is shown in equation (2), which is the objective function 1, to be maximised in the 2-objective problem.

$$A = \frac{\sum_i t_{o_i}}{\sum_i t_{o_i} + \sum_j t_{r_j}}. \quad (2)$$

In equation (2), i expresses the count of operation times, t_{o_i} indicates the i-th operation time with the hour as the unit of measurement (it can be a time to failure or a time to initiate a preventive maintenance task), the count of recovery times is expressed by j and t_{r_j} is the j-th recovery time with the hour as the unit of measurement (due to a repair or a preventive maintenance task). For the availability model, some considerations are taken into account:

(i) Operating or recovery states are the feasible states for the gadgets.

(ii) These gadgets are not dependent, so the failure of one of them does not affect to the other one.

(iii) A corrective maintenance activity consists of replacing the failed gadget.

(iv) Preventive and corrective maintenance tasks are initiated immediately after stopping,

(v) A gadget is giving back to its as-good-as-new state after both preventive and corrective maintenance tasks.

Equation (3) shows the cost model adopted in the present paper when two objectives are considered. This is objective function 2, to be minimised in the 2-objective problem.

$$C = \sum_k \left(Ca_k + \sum_{k_i} \left(D_{k_i} + Cc_{k_i} \right) + \sum_{k_j} Cp_{k_j} \right), \quad (3)$$

where C is the Cost (€), k expresses each one of the gadgets to consider for the design of the system, Ca_k is the acquisition cost in relation to the k-th gadget, k_i denotes the i-th corrective maintenance activity regarding the k-th gadget, D_{k_i} is the cost in relation to the i-th replace for the k-th gadget, Cc_{k_i} is the cost regarding the i-th corrective maintenance activity in relation to the k-th gadget, k_j denotes the j-th preventive maintenance activity regarding the k-th gadget, and Cp_{k_j} is the cost in relation to the j-th preventive maintenance activity regarding the k-th gadget. To compute Cc_{k_i} and Cp_{k_j} the number of hours that are dedicated to each maintenance activity and the cost per hour regarding the respective maintenance activities must be multiplied.

The cost model from equation (3) considers jointly the acquisition cost and the operational cost. In order to decompose such a model, the acquisition cost and the operational cost are considered as separated objectives when the 3-objective problem is solved. Therefore, equations (2), (4), and (5) (objective functions 1, 2, and 3, respectively) are employed to solve the 3-objective problem.

$$C_{\text{ac}} = \sum_k (Ca_k), \quad (4)$$

$$C_{\text{op}} = \sum_k \left(\sum_{k_i} \left(D_{k_i} + Cc_{k_i} \right) + \sum_{k_j} Cp_{k_j} \right), \quad (5)$$

where C_{ac} is the acquisition cost and C_{op} is the operational cost. To estimate the maintenance costs, a cost per hour is considered for both corrective and preventive maintenance activities. Recovery times regarding corrective maintenance tasks present uncertainty and are longer than recovery times due to preventive maintenance tasks. Preventive maintenance tasks are planned for shutdowns. Therefore, a better control can be considered.

Depending on the architectural design of the system, the number of decision variables changes. There are decision variables dedicated to design and dedicated to maintenance. Decision variables dedicated to design (D) establish whether to include a redundant gadget. Decision variables in relation to maintenance (M) establish the periodic time to initiate a maintenance task regarding each gadget included in the architectural design. More details are shown later when the case study is solved.

The decision variables have lower and upper values, as shown in the following equations:

$$0 \leq D \leq 1, \quad (6)$$

$$\text{TM}_{\min} \leq M \leq \text{TM}_{\max}, \quad (7)$$

where $\text{TM}_{\min}$ is the minimum time to initiate a preventive maintenance activity regarding a specific gadget and $\text{TM}_{\max}$ is the maximum time to initiate a preventive maintenance activity regarding such a gadget.

2.2. Simulating the Life Cycle of the System. To compute the objective functions, the functionability profile or life cycle of the system must be simulated. For this purpose, a population of individuals or candidate solutions is suggested by the multiobjective evolutionary algorithm. These individuals codify both the system design and its preventive maintenance strategy. The maintenance strategy contains the periodic timing to initiate preventive maintenance tasks in relation to each gadget integrated into the design. Based on such a maintenance strategy, the life cycle of the system can be created by employing discrete event simulation. Therefore, having information regarding how to depict both operation (t_{o_i}) and recovery (t_{r_i}) times is vital. As explained above, operation times can be times to failure (TF) or times to initiate a preventive maintenance task (TM), while recovery times can be times to repair (TR) or times to carry out a preventive maintenance activity (TCM). The life cycle of the gadgets must be built to create the life cycle of the system. Figure 1 illustrates the process of creating the life cycle of the system. It is explained as follows:

(1) The duration of the life cycle of the system is previously fixed. The process must cover the gadgets included in the system design.

(2) The life cycle (LC) of a gadget must be initiated.

(3) The multiobjective evolutionary algorithm provides the time to initiate a preventive maintenance activity (TM), which is taken out of the respective variable of the chromosome. Next, a time to carry out such a preventive maintenance task (TCM) must be randomly created. Such a random value is obtained from the density function in relation to the time to carry out a preventive maintenance activity.

(4) An operation time to failure (TF) must be randomly created from the failure density function.

(5) If TM is smaller than TF, the preventive maintenance activity will be carried out before failing. Therefore, the TM value (as an operation time) is used to build this segment of the life cycle of the gadget. The TM value must be followed by the TCM value (as a recovery time).

(6) If TM is bigger than TF, the failure occurs before initiating the preventive maintenance activity. In such a case, a time to repair (TR) must be randomly generated from the repair density function. Therefore, this segment of the life cycle of the gadget is built by the TF value (as an operation time) followed by the TR value (as a recovery time).

(7) The steps 4 to 6 must be replicated until the end of the life cycle of the gadget.

(8) The steps 2 to 7 must be replicated until the life cycles of all gadgets have been built.

(9) Finally, the life cycle of the system is created in relation to the system architecture.

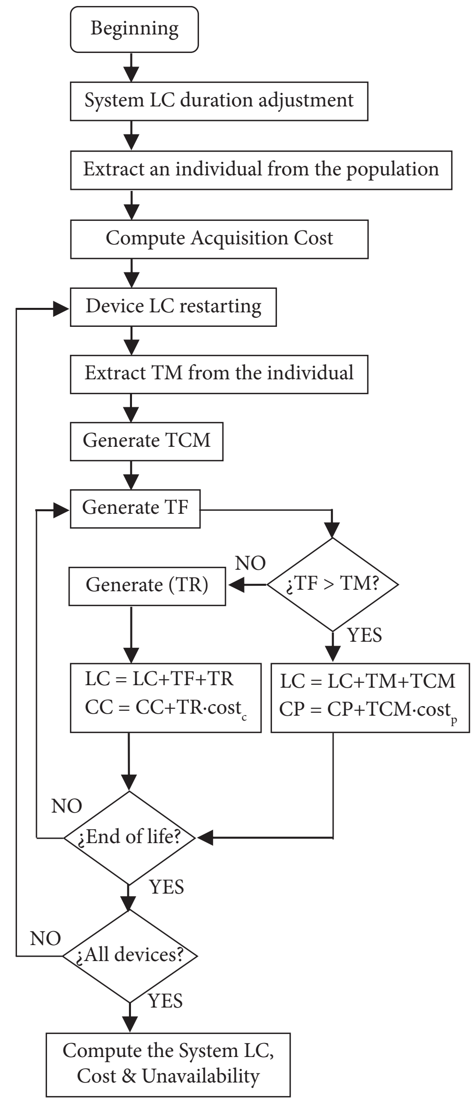

Figure 1: Creating the life cycle of the system.

Once the life cycle of the system is built, the availability can be computed by using equation (2) Some considerations must be taken into account regarding the cost computation. When the 2-objective problem is solved, the cost model includes the acquisition and the operational costs equation (3). Nevertheless, both the acquisition cost and the operational cost are managed as different objectives when the 3-objective problem is considered (equations (4) and (5), respectively).

2.3. Multiobjective Optimisation. In this paper, evolutionary algorithms are used as optimisation methods. Such algorithms are based on populations of individuals, which are solutions to the problem. Such individuals are symbolised by chromosomes. In Ref. [26], detailed information regarding multiobjective evolutionary optimisation algorithms is supplied. In the present study, each individual is formed by a string of variables (both reals and binaries, attending to the coding) where both the system design and its periodic times to initiate a preventive maintenance task are coded. It is explained in detail in the case study section. When a multiobjective approach is considered, the solution to the problem arises from a set of solutions. The best compromise among objectives is represented by such a set [26, 27]. A minimisation multiobjective problem is described by equation:

$$\min_{x} f(x) = \min_{x} [f_1(x), \ldots, f_k(x)]. \quad (8)$$

The k functions must be simultaneously minimised when the problem is defined by this way. In the current study, both the availability of the system and its cost are considered as objectives to be maximised and minimised, respectively. When the 2-objective problem is solved, such objectives must be computed by employing equations (2) and (3), respectively. Equations (2), (4), and (5) must be employed when the 3-objective problem is solved. When the 2-objective problem is multiobjectivisated, the cost is decomposed in order to consider separate the acquisition cost equation (4) and the operational cost equation (5). Furthermore, in this study, limited values are considered regarding times to failure, times to initiate preventive maintenance tasks, times to repair, and times to conduct preventive maintenance activities.

Nowadays, multiobjective evolutionary optimisers (EMOs) can be classified into three groups [26, 28]:

(i) Indicator-based selection EMO: This kind of optimisers employs some unary indicator to lead the search.

(ii) Decomposition/aggregated-based selection EMO: This kind of optimisers decomposes the search space, optimising a set of scalarizing functions.

(iii) Dominance-based selection EMO: This kind of optimisers employs the Pareto dominance selection.

In order to solve the problem, representative algorithms based on the indicator-based selection and the dominance-based selection paradigms were chosen from the state-of-the-art. Concretely, in the present research, the multiobjective evolutionary algorithms employed are as follows:

(i) The S-metric selection evolutionary multiobjective optimisation algorithm (SMS-EMOA) [29], which uses the multiobjective selection based on dominated hypervolume, as a representative method of the indicator-based selection EMO.

(ii) The nondominated sorting genetic algorithm II (NSGA-II) [30], which uses the Pareto dominance criterion, as a representative method of the dominance-based selection EMO.

SMS-EMOA and NSGA-II are state-of-the-art standard solvers to face real-world multiobjective optimisation problems [26, 31]. These methods employ simulated binary crossover [32] to create new individuals when real encoding is used. Therefore, these multiobjective evolutionary algorithms are employed to optimise the system design and its maintenance strategy. To do that, it is possible to minimise both the system unavailability (equivalent to maximising the system availability) and the cost.

3. The Case Study

3.1. Substation Layout and Data Description. The case study consists of applying the methodology to a specific section of a subsystem of a substation automation system (SAS). The T1-1 substation design [4] is a small transmission substation, which is designed to transform energy (220 kV $\longrightarrow$ 132 kV). The substation is formed by 5 bays (1 for bus, 3 bay lines, and 1 for transformer). For one of the line bays, the methodology is employed for the combined optimisation of the design and its maintenance strategy. A star topology has been assumed [2] for the connection of the equipment in the line bay. Such a circumstance indicates that the Cnt. IED (control intelligent electronic device), the MU (merging unit), and the Prt. IED (protection intelligent electronic device) are connected to the ESW (ethernet switch). Furthermore, a TS (time synchronisation source) is linked to the MU [4]. In Figure 2, the common architecture for a line bay is shown.

Figure 3 shows the reliability block diagram. It can be seen that, as a redundant gadget, a second Prt. IED can be considered. The testing and calibration of protective relays, as well as the verification of system telecommunications equipment, are examples of typical preventive maintenance activities for such gadgets [33].

In order to apply the methodology, specific data about the system's gadgets are needed. This information is defined as follows (the hour is used as the unit of measurement):

(1) TF_{min} = Minimum value for the time to failure regarding a gadget.

(2) TF_{max} = Maximum value for the time to failure regarding a gadget.

(3) TF_{λ} = Failure rate regarding a gadget.

(4) TR_{min} = Minimum time to repair or time to carry out a corrective maintenance task for a gadget.

(5) TR_{max} = Maximum time to repair or time to carry out a corrective maintenance task for a gadget.

(6) TR_{μ} = Mean in relation to the normal distribution that describes the time to conduct a corrective maintenance (time to repair) regarding a gadget.

(7) TR_{σ} = Standard deviation in relation to the normal distribution that describes the time to conduct a corrective maintenance (time to repair) regarding a gadget.

(8) TM_{min} = Minimum time to initiate a preventive maintenance activity regarding a gadget. Before this time, initiating a preventive maintenance task for a gadget is not required.

(9) TM_{max} = Maximum time to initiate a preventive maintenance activity regarding a gadget. Initiating a preventive maintenance task for a gadget is a recklessness after this time.

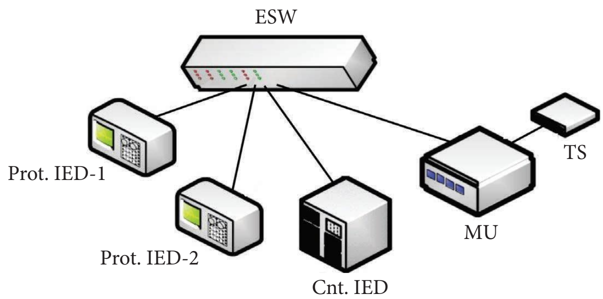

Figure 2: Star topology for a line bay.

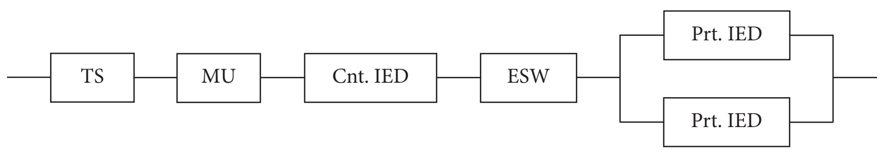

Figure 3: Reliability blocks diagram for a line bay.

(10) TCM_{min} = Minimum time to carry out a preventive maintenance activity in relation to a gadget. It is the minimum time needed to conduct such a preventive maintenance task.

(11) TCM_{max} = Maximum time to carry out a preventive maintenance activity in relation to a gadget. It is the maximum time needed to conduct such a preventive maintenance task.

The case study was conducted over a mission time or life cycle of 525,600 hours. The corresponding set of values can be found in Table 1. The costs were provided by the Instituto Universitario de Sistemas Inteligentes y Aplicaciones Numéricas en Ingeniería (SIANI) and the Instituto Superior Técnico (IST) [34], from the Universidad de Las Palmas de Gran Canaria and Universidade de Lisboa, respectively. The failure rates (λ) were taken from the studies conducted by Scheer and Dolezilek [35] and CISCO [36]. Both studies employ reliability data referring to solvent organisations and manufacturers. Such entities provide reliability data based on research and experience in real-world power systems. The failure rates can be obtained from the mean time between failures (MTBF) provided by these references ($\text{MTBF} = 1/\lambda$). When the devices were not directly cited, an approximation by similitude was employed (in the case of the merging unit, λ for and IED were considered). In the case of the time synchronisation source, λ for a generic network element was used. Given the flexibility of the methodology, reliability data provided by other manufacturers could be used. The means about the time to repair (TR_{μ}) were taken from Kanabar and Sidhu [4] and CISCO [36]. The TF_{min} value was taken as 1 hour, and the TF_{max} value was taken as the mission time or life cycle. However, the TM_{max} value limits the TF_{max} value since the operation time considered is the smaller one. According to the data sources, the TR_{min} value was set at 2 hours for the MU, Cnt. IED, ESW, and Prt.IED, and 1 hour for the TS. Since a normal distribution with μ as the mean considered regarding the time to repair, a mathematical relationship was employed to set the TR_{σ}. For a normal distribution, it is well known that 99.7% of values fall within the interval $\mu \pm 3\sigma$. Therefore, it was considered to define both the TR_{σ} value and the TR_{max} value. The TM_{max} value was set to 6 months, as stated by NERC 2007 [37]. Moreover, the TM_{min} value was set at half. Finally, the TCM_{min} value and the TCM_{max} value were set at half of the TR_{min} value and the TR_{max} value, respectively.

As it was exposed above, the system availability and the costs are the objectives to be maximised and minimised, respectively. To do that

(i) For each gadget, the optimum periodic time to initiate a preventive maintenance task must be determined (optimisation of the maintenance strategy), and

(ii) It must be decided whether or not to include a Prt. IED as a redundant gadget (optimisation of the automatic selection of gadgets). To do this, it is necessary to evaluate the design alternatives.

3.2. Optimisation Details. As explained above, evolutionary algorithms (EAs) use a population of individuals that denote possible solutions to the problem. In this case, both binary and real coding are used. Therefore, two codifications are explored:

(i) When real coding is used: A string of real numbers, which take values between 0 and 1, is used to represent each individual. Such a string is coded by using the variables $[D_1 M_1 M_2 M_3 M_4 M_5 M_6]$. D_1 indicates whether the redundant gadget (Prt. IED2) is included in the design while M_1 to M_6 indicate the optimum time to initiate a preventive maintenance activity regarding each gadget, respectively. However, to compute the objective functions, such variables must be transformed:

Table 1: Data set regarding the gadgets.

Parameter	Value	Source
Preventive maintenance	110 €/h	SIANI-IST
Corrective maintenance	100 €/h	SIANI-IST
TS acquisition cost	7,000 €	IST [34]
TS TF_{min}	1 h	—
TS TF_{max}	525,600 h	Mission time
TS TF_{λ}	$0.1 \cdot 10^{-6}$ failures/h	CISCO [36]
TS TR_{min}	1 h	—
TS TR_{max}	7 h	$TR_{\mu} + 3 \cdot TR_{\sigma}$
TS TR_{μ}	4 h	CISCO [36]
TS TR_{σ}	1 h	$(TR_{\mu} - TR_{min})/3$
TS TM_{min}	2,190 h	$TM_{max}/2$
TS TM_{max}	4,380 h	NERC 2007 [37]
TS TCM_{min}	1 h	Round $(TR_{min}/2)$
TS TCM_{max}	4 h	Round $(TR_{max}/2)$
MU acquisition cost	3,500 €	IST [34]
MU TF_{min}	1 h	—
MU TF_{max}	525,600 h	Mission time
MU TF_{λ}	$6.0047 \cdot 10^{-6}$ failures/h	Scheer and Dolezilek [35]
MU TR_{min}	2 h	—
MU TR_{max}	14 h	$TR_{\mu} + 3 \cdot TR_{\sigma}$
MU TR_{μ}	8 h	Kanabar and Sidhu [4]
MU TR_{σ}	2 h	$(TR_{\mu} - TR_{min})/3$
MU TM_{min}	2,190 h	$TM_{max}/2$
MU TM_{max}	4,380 h	NERC 2007 [37]
MU TCM_{min}	1 h	Round $(TR_{min}/2)$
MU TCM_{max}	7 h	Round $(TR_{max}/2)$
Cnt.IED acquisition cost	3,537.50 €	IST [34]
Cnt.IED TF_{min}	1 h	—
Cnt.IED TF_{max}	525,600 h	Mission time
Cnt.IED TF_{λ}	$6.0047 \cdot 10^{-6}$ failures/h	Scheer and Dolezilek [35]
Cnt.IED TR_{min}	2 h	—
Cnt.IED TR_{max}	14 h	$TR_{\mu} + 3 \cdot TR_{\sigma}$
Cnt.IED TR_{μ}	8 h	Kanabar and Sidhu [4]
Cnt.IED TR_{σ}	2 h	$(TR_{\mu} - TR_{min})/3$
Cnt.IED TM_{min}	2,190 h	$TM_{max}/2$
Cnt.IED TM_{max}	4,380 h	NERC 2007 [37]
Cnt.IED TCM_{min}	1 h	Round $(TR_{min}/2)$
Cnt.IED TCM_{max}	7 h	Round $(TR_{max}/2)$
ESW acquisition cost	2,600 €	IST [34]
ESW TF_{min}	1 h	—
ESW TF_{max}	525,600 h	Mission time
ESW TF_{λ}	$9.9265 \cdot 10^{-6}$ failures/h	Scheer and Dolezilek [35]
ESW TR_{min}	2 h	—
ESW TR_{max}	14 h	$TR_{\mu} + 3 \cdot TR_{\sigma}$
ESW TR_{μ}	8 h	Kanabar and Sidhu [4]
ESW TR_{σ}	2 h	$(TR_{\mu} - TR_{min})/3$
ESW TM_{min}	2,190 h	$TM_{max}/2$
ESW TM_{max}	4,380 h	NERC 2007 [37]
ESW TCM_{min}	1 h	Round $(TR_{min}/2)$
ESW TCM_{max}	7 h	Round $(TR_{max}/2)$
Prt.IED acquisition cost	3,537.50 €	IST [34]
Prt.IED TF_{min}	1 h	—
Prt.IED TF_{max}	525,600 h	Mission time
Prt.IED TF_{λ}	$6.0047 \cdot 10^{-6}$ failures/h	Scheer and Dolezilek [35]
Prt.IED TR_{min}	2 h	—
Prt.IED TR_{max}	14 h	$TR_{\mu} + 3 \cdot TR_{\sigma}$
Prt.IED TR_{μ}	8 h	Kanabar and Sidhu [4]
Prt.IED TR_{σ}	2 h	$(TR_{\mu} - TR_{min})/3$
Prt.IED TM_{min}	2,190 h	$TM_{max}/2$
Prt.IED TM_{max}	4,380 h	NERC 2007 [37]
Prt.IED TCM_{min}	1 h	Round $(TR_{min}/2)$
Prt.IED TCM_{max}	7 h	Round $(TR_{max}/2)$

(a) D_1 must be rounded at the nearest integer. Therefore, if its value is 1 a redundant Prt. IED is included in the design. Conversely, the value of 0 indicates the noninclusion of the redundant Prt. IED in the design.

(b) Employing equation (9), the variables M_1 to M_6 must be scaled, where TM_i is the true time to initiate a preventive maintenance activity for the i-th line bay gadget, M_i denotes the value of the decision variable in relation to the i-th line bay gadget, and finally, $\mathrm{TM}_{\max_i}$ and $\mathrm{TM}_{\min_i}$ are the limit values regarding TM_i for the i-th line bay gadget ($1 \le i \le 6$).

$$\mathrm{TM}_i = \mathrm{round}\left(\mathrm{TM}_{\min_i} + M_i \bullet \left(\mathrm{TM}_{\max_i} - \mathrm{TM}_{\min_i}\right)\right), \tag{9}$$

(ii) When binary coding is used: A string of binary numbers forms each individual in the population. Such numbers can take values of 1 or 0. The string consists of 73 bits, where

(a) D_1 indicates whether a redundant Prt. IED is included in the system design. Again, the value of 1 involves the inclusion of the redundant Prt. IED in the design, and the value of 0 indicates the opposite.

(b) M_2 to M_{13} represent the optimum time to initiate a preventive maintenance activity in relation to the gadget TS. In order to obtain its true TM value, a binary scale to represents the numbers from $\mathrm{TM}_{\min}$ and $\mathrm{TM}_{\max}$ values is required. For instance, the value for $\mathrm{TM}_{\min_{TS}}$ is 2,190 hours, and it is 4,380 hours for $\mathrm{TM}_{\max_{TS}}$. Hence, the necessary scale steps are 4,380−2,190 = 2,190, where 2,190 hours are represented by the step zero and 4,380 hours are represented by the step 2,189. In order to cover 2190 steps, the condition $2^n > 2,190$ must be satisfied, where n is the bits number. Consequently, 12 bits are needed. Whereas $2^{12} = 4,096$ steps are available, only 2,190 steps are needed. Therefore, a relationship between such scales must be employed. In the scale of 4,096 steps, each one represents 2,190 ÷ 4,096 = 0.53466796875 steps regarding the scale of 2,190 steps. Thus, the transformation provided by equation (10) must be used to obtain the true time to initiate a preventive maintenance activity.

$$\mathrm{TM}_i = \mathrm{round}\left(\mathrm{TM}_{\min_i} + M_i \bullet (0.53466796875)\right), \tag{10}$$

(c) The process must be repeated in order to obtain the true TM value for the MU (bits M_{14} to M_{25}), the Cnt. IED (bits M_{26} to M_{37}), the ESW (bits M_{38} to M_{49}), the Prt. IED1 (bits M_{50} to M_{61}), and the Prt. IED2 (bits M_{62} to M_{73}).

Table 2: Parameters regarding the optimisation process.

Method	Encoding	PrM	disM	PrC	disC
SMS-EMOA	Real	0.5 1.0 1.5	20	1	20
SMS-EMOA	Binary	0.5 1.0 1.5	—	1	—
NSGA-II	Real	0.5 1.0 1.5	20	1	20
NSGA-II	Binary	0.5 1.0 1.5	—	1	—

Table 2 shows the multiobjective algorithms employed and their parameters.

Due to the fact that multiobjective evolutionary algorithms require intensive computation, the parameters were chosen on the basis of the most relevant factors related to a proper balance of exploration-exploitation. They were set from previous studies conducted by the authors of this research as explained above [22–24]. The parameters are as follows:

(i) Mutation probability (PrM): Number of genes mutating. 1/(decision variables) is considered as the primary value. Two additional values were utilized for comparison, one being lower (0.5/(decision variables)) and the other higher (1.5/(decision variables)) than the primary value. Furthermore, on the one hand, simulated binary crossover is used as a recombination mechanism when the real code is employed. On the other hand, 2-point crossover is used as a recombination mechanism when the binary code is employed.

(ii) Mutation distribution (disM): When the real code is used, this parameter denotes the distribution index of polynomial mutation. A standard value of 20 was established after confirming its minimal impact through various alterations.

(iii) Crossover probability (PrC): When the simulated binary crossover is employed, this parameter denotes the probability of doing crossover. When new individuals are created, the crossover operator presents a considerable impact. It is set to 1 to promote the effect from such an operator.

(iv) Crossover distribution (disC): This is the crossover distribution index when the simulated binary crossover is employed. A standard value of 20 was established after confirming its minimal impact through various alterations.

A population size of 150 individuals was considered. Six configurations were processed, and 21 executions each were carried out for statistical purposes. 10,000,050 evaluations of the objective functions were computed (stopping criterion).

Several scale factors were taken into account to normalize the values of the objective functions. These values were obtained by evaluating the objective functions at the start of the process. This approach anticipates that the values of the objective functions will improve as the simulation process progresses. To address the 2-objective problem, the following scale factor values were set:

(i) A scale factor of 740,000 € was considered when evaluating the cost.

(ii) A scale factor of 0.01 was used when calculating the unavailability.

When the 3-objective problem was solved, the set values of the scale factors were as follows:

(i) A scale factor of 24,000 € was applied when assessing the acquisition cost.

(ii) A scale factor of 740,000 € was employed during the evaluation of the operational cost.

(iii) A scale factor of 0.01 was considered when calculating the unavailability.

Finally, a reference point must be established to compute the hypervolume, depending on the number of objectives. The reference points should encompass the limits set by the scale factors. In this case, the points (2, 2) and (2, 2, 2) were used as reference points. The Platform PlatEMO [38] was employed to optimise the problem, which includes multitude of multiobjective evolutionary algorithms, a variety of multiobjective test problems and various performance indicators. Hence, the design and maintenance strategy problem was developed and integrated into PlatEMO.

4. Results and Discussion

The experiments were simulated using a high-performance computer (HPC). Such a HPC has six calculation nodes. Furthermore, it has a front-end node. Two processors Intel Xeon E5645 Westmere-EP form each node. Each processor consists of six cores with 48 GB of RAM.

Useful information is provided from the results:

(1) Information about the computational process is supplied. The computational cost for simulating each method and coding is supplied.

(2) Regarding each configuration, the evolution of the average hypervolume [39] (HV) value (in twenty-one executions) is supplied.

(3) For the distribution of hypervolume values finally reached, box plots are supplied.

(4) Some statistical measurements are displayed. Such statistical measurements are, for the hypervolume, the average, median, maximum, minimum, and standard deviation.

(5) To identify significant differences among the methods' performance, a hypothesis test is carried out. The Friedman's test is employed to detect differences among performances and rejecting the null hypothesis (H_0) in such a case. A post hoc test is conducted when such differences are detected. The lowest significant value to reject H_0 is indicated by the p value. The p value provides evidence about the significance of a test: a p value lower than 0.05 implies the rejection of H_0. Benavoli et al. [40] described the procedure to carry out the pairwise comparisons.

(6) The Hypervolume is evaluated [41] for the accumulated nondominated solutions. The best balance among objectives is supplied by these solutions.

Next the results are exposed.

4.1. 2-Objective Problem Results. Each execution consumed an average time of 3 days and 16 minutes. The whole process involves a sequential time of 2 years, 28 days, and 20 hours. The simulation process is possible due to the parallel process allowed by the HPC. Columns 1 to 4 (Table 3) show the correlation between the identifiers of configurations and the methods.

Figure 4 shows the evolution of the average hypervolume relative to the number of evaluations. At the end of the process, the highest average hypervolume value is produced by the configuration identified as ID2, which uses real coding and 1.0 gene per chromosome with the NSGA-II method.

In Figure 5, box plots are employed to show the distribution of hypervolume values finally achieved. Table 3 (columns 5 to 9) summarises the statistical information provided by these box plots. The best average hypervolume value is achieved by the configuration identified as ID2, which uses real coding with the NSGA-II method and 1.0 gene per chromosome. Furthermore, the best median hypervolume value is achieved by the configuration identified as ID7, which employs real coding with the SMS-EMOA method and 0.5 gene per chromosome. The best maximum hypervolume value is provided by the configuration identified as ID1, which uses real coding with the NSGA-II method and 0.5 gene per chromosome. The configuration identified as ID9, which uses real coding with the SMS-EMOA method and 1.5 gene per chromosome, supplies the best minimum hypervolume value. Finally, the smallest standard deviation value is found by the configuration identified as ID4, which uses binary coding, with 0.5 gene per chromosome and the NSGA-II method.

Next, it is necessary to check whether one configuration works better than another. Therefore, a hypothesis test of statistical significance is performed. Employing Friedman's test, the average ranks were computed and ordered. In Table 3 (column 10), such average ranks are shown. The best average rank (when the problem considers maximising the hypervolume, the average rank must be as low as possible) is achieved by the configuration identified as ID2, which employs real coding and 1.0 gene per chromosome for the NSGA-II method. Nevertheless, the obtained p value of 0.2787 does not allow the rejection of H_0 (p value >0.05). Therefore, it cannot be concluded that "any one configuration works better than another."

Table 3: Statistical analysis (2-objective problem) of hypervolume indicator.

ID	Method	Encoding	Mutation	Average	Median	Maximum	Minimum	Standard deviation	Average rank (Friedman test)
1	NSGA-II	Real	0.5	3.4404	3.4340	**3.5192**	3.4044	0.0258	7.5714
2	NSGA-II	Real	0.1	**3.4495**	3.4456	3.4898	3.4141	0.0192	**4.7619**
3	NSGA-II	Real	1.5	3.4439	3.4356	3.4786	3.4160	0.0189	6.0952
4	NSGA-II	Binary	0.5	3.4393	3.4428	3.4645	3.4107	**0.0126**	6.1428
5	NSGA-II	Binary	1.0	3.4397	3.4370	3.4746	3.4119	0.0149	6.8095
6	NSGA-II	Binary	1.5	3.4332	3.4340	3.4674	3.4064	0.0149	7.8571
7	SMS-EMOA	Real	0.5	3.4471	**3.4474**	3.4800	3.4166	0.0150	5.3333
8	SMS-EMOA	Real	1.0	3.4391	3.4364	3.4812	3.4125	0.0163	6.7142
9	SMS-EMOA	Real	1.5	3.4389	3.4421	3.4635	3.4111	0.0144	6.6666
10	SMS-EMOA	Binary	0.5	3.4414	3.4368	3.4916	3.4075	0.0213	7.0952
11	SMS-EMOA	Binary	1.0	3.4413	3.4391	3.4824	3.4095	0.0193	6.4761
12	SMS-EMOA	Binary	1.5	3.4401	3.4373	3.4747	**3.4215**	0.0145	6.4761
p value									0.2787

Best values (column-wise), in bold type.

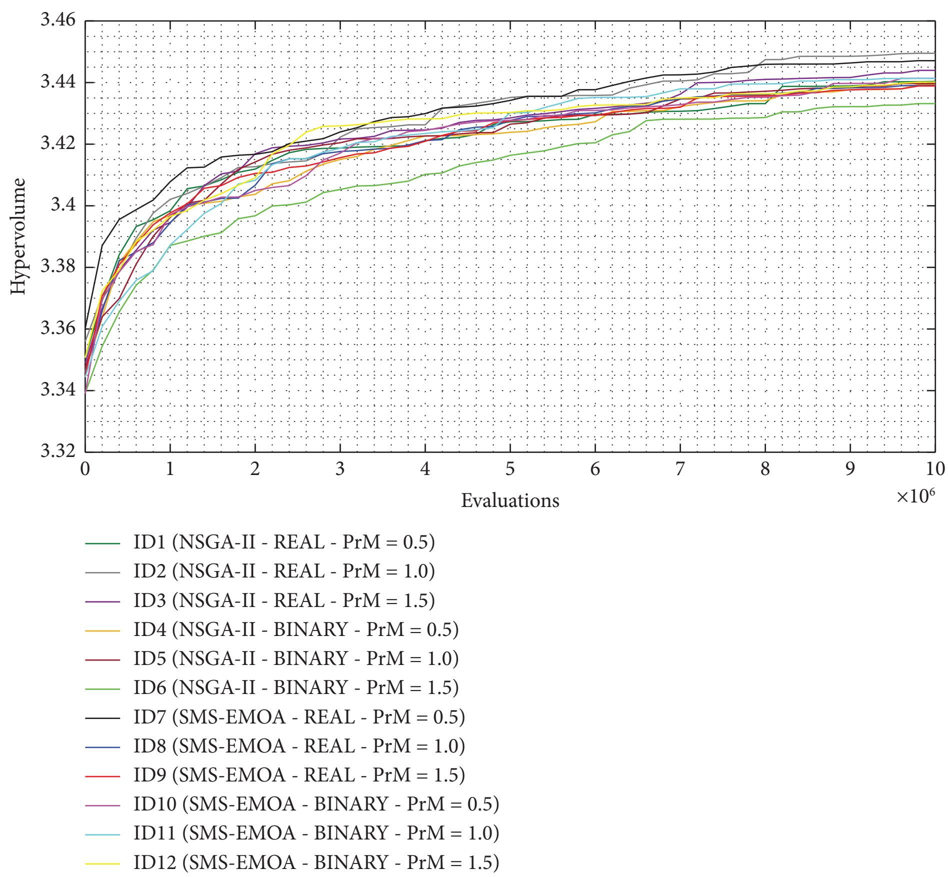

Figure 4: Average hypervolume vs. number of evaluations (2-objective problem).

Figure 6 displays the nondominated solutions. These solutions were obtained once the whole simulation process was completed, and they are described in Table 4. The solutions with worse unavailability are firstly ordered. In such a table, the unavailability (Q) is shown in the second column, the cost in the third column, and the optimum times to initiate a preventive maintenance task regarding each gadget are shown from columns four to nine, respectively.

It can be seen that the less reliable and inexpensive solutions are identified as ID1 and ID2 in Table 4, and they are marked as O in Figure 6. These are designs without a redundant Prt. IED. Therefore, for the redundant Prt. IED, Table 4 does not present a value regarding the time to initiate a preventive maintenance activity. On the contrary, the more reliable and expensive solutions are identified as ID3 to ID8 in Table 4, and they are marked as × in Figure 6. The inclusion of a redundant Prt. IED is considered for such solutions.

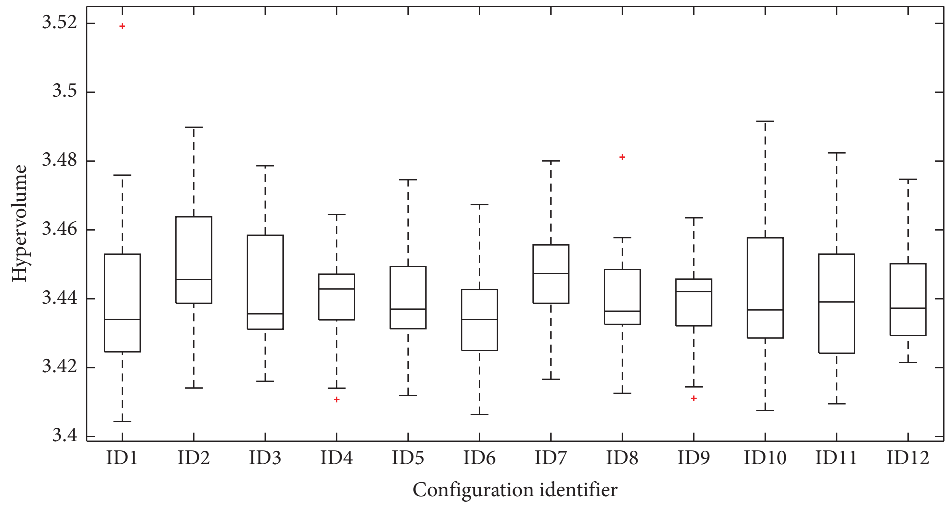

FIGURE 5: Box plots for the achieved hypervolume (2-objective problem, the identifiers as in Table 3).

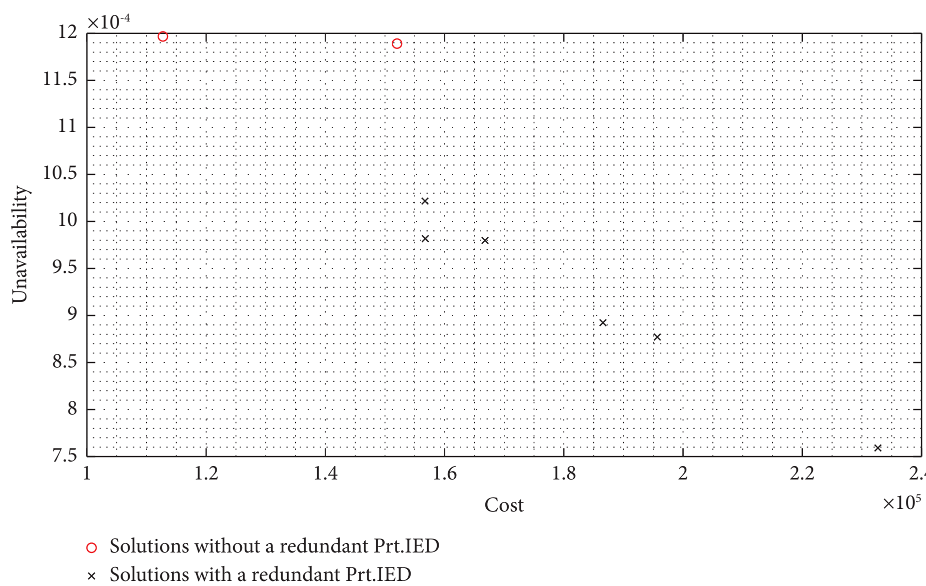

FIGURE 6: Accumulated nondominated front (2-objective problem).

TABLE 4: Nondominated solutions obtained for the 2-objective problem.

ID	Q	Cost (€)	TS (h)	Mu (h)	Cnt. IED (h)	ESW (h)	Prt. IED (h)	Prt. IED (h)
1	0.001197	112,750.00	4,369	4,350	4,298	4,342	4,322	0
2	0.001189	152,022.50	4,353	4,380	4,173	4,377	4,380	0
3	0.001022	156,712.50	4,372	4,282	4,352	4,239	4,235	3,752
4	0.000982	156,762.50	4,380	4,333	4,369	4,321	4,317	3,306
5	0.000980	166,782.50	4,349	4,360	4,337	4,285	4,022	3,250
6	0.000892	186,565.00	4,380	4,380	4,082	4,195	4,271	3,761
7	0.000877	195,675.00	4,376	4,245	4,309	4,376	4,183	4,129
8	0.000759	232,682.50	4,349	4,377	4,380	4,380	2,805	3,279

The maximum value for the time to initiate a preventive maintenance activity is 4,380 hours (from Table 1, see TM_{max} values). It can be seen that the times provided by the algorithms in Table 4 are close to such a value. Therefore, the time among preventive maintenance activities is being maximised as much as possible by the optimisers. Nevertheless, for the main Prt. IED, a value of 2,805 hours is shown in the solution ID8 (see Table 4). This means that more preventive maintenance activities must be conducted, so more investment is needed.

Table 5: Statistical analysis (3-objective problem) of hypervolume indicator.

ID	Method	Encoding	Mutation	Average	Median	Maximum	Minimum	Standard deviation	Average rank (Friedman test)
1	NSGA-II	Real	0.5	4.0442	4.0420	4.0862	3.9998	0.0229	6.2857
2	NSGA-II	Real	0.1	4.0422	4.0394	4.0856	4.0144	0.0167	6.4761
3	NSGA-II	Real	1.5	4.0377	4.0372	4.0613	4.0066	0.0158	7.6190
4	NSGA-II	Binary	0.5	4.0473	4.0445	4.0716	4.0184	0.0151	5.4285
5	NSGA-II	Binary	1.0	4.0453	4.0413	4.0948	4.0053	0.0228	5.9523
6	NSGA-II	Binary	1.5	4.0436	4.0430	**4.1269**	4.0002	0.0265	6.4761
7	SMS-EMOA	Real	0.5	4.0527	4.0480	4.1046	4.0160	0.0259	5.3809
8	SMS-EMOA	Real	1.0	**4.0531**	**4.0512**	4.1035	**4.0255**	0.0191	**4.9523**
9	SMS-EMOA	Real	1.5	4.0487	4.0472	4.0892	4.0177	0.0192	5.8095
10	SMS-EMOA	Binary	0.5	4.0382	4.0383	4.1104	4.0056	0.0261	7.5714
11	SMS-EMOA	Binary	1.0	4.0373	4.0352	4.0704	4.0168	**0.0147**	7.3809
12	SMS-EMOA	Binary	1.5	4.0301	4.0308	4.0603	4.0069	0.0148	8.6666
p value									0.0260

Best values (column-wise), in bold type.

Finally, the accumulated hypervolume for the front of solutions achieves a value of 3.5239, which was computed as described in Ref. [41]. Therefore, this value overcomes the value of 3.5192, which is the maximum value in Table 3. This is expected because the accumulated hypervolume is obtained considering the nondominated solutions from all configurations.

4.2. 3-Objective Problem Results. Each execution consumed an average time of 4 days, 3 hours, and 5 minutes. Columns 1 to 4 (Table 5) show the correlation between the identifiers of configurations and the methods.

Figure 7 shows the evolution of the average hypervolume relative to the number of evaluations. At the end of the process, the highest average hypervolume value is produced by the configuration identified as ID8, which uses real coding with 1.0 gene per chromosome and the SMS-EMOA method.

In Figure 8, box plots are employed to show the distribution of hypervolume values finally achieved. Table 5 (columns 5 to 9) summarises the statistical information provided by these box plots. The configuration identified as ID8, which employs real coding with 1.0 gene per chromosome and the SMS-EMOA method, achieves the best average, median, and minimum hypervolume values. On the other hand, the configuration identified as ID6, which uses binary coding with 1.5 gene per chromosome and the NSGA-II method, achieves the best maximum hypervolume value. Finally, the smallest standard deviation is presented by the configuration identified as ID11, which considers binary coding with 1.0 gene per chromosome and the SMS-EMOA method.

Next, it is necessary to check whether one configuration works better than another. Therefore, a hypothesis test of statistical significance is performed. Employing Friedman's test, the average ranks were computed and ordered. In Table 5 (column 10), such average ranks are shown. The best average rank is supplied by the configuration identified as ID8, which uses real coding with 1.0 gene per chromosome and the SMS-EMOA method. Nevertheless, the obtained p value of 0.0260 allows the rejection of H_0 (p value <0.05). Hence, it can be concluded that "at least the configuration ID8 works better than some other configuration." The Wilcoxon signed-rank test was employed to carry out pairwise comparisons. In Table 6, the outcomes of using such a test are shown. The configuration identified as ID8 works better than the configuration identified as ID3, which uses real coding with 1.5 gene per chromosome and the NSGA-II method; the configuration identified as ID11, which employs binary coding with 1.0 gene per chromosome and the SMS-EMOA method; and the configuration identified as ID12, which uses binary coding with 1.5 gene per chromosome and the SMS-EMOA method.

Figure 9 displays the nondominated solutions. These solutions were obtained once the whole simulation process was completed, and they are described in Table 7. The solutions with worse unavailability are firstly ordered. In such a table, the unavailability (Q) is shown in the second column, the operational cost is shown in the third column, the acquisition cost is shown in the fourth column, and the optimum times to initiate a preventive maintenance task in relation to each gadget are shown in columns five to ten, respectively.

It can be seen that the less reliable and inexpensive solutions are identified as ID1 to ID3 in Table 7, and they are marked as O in Figure 9. These are designs without a redundant Prt. IED. Therefore, for the redundant Prt. IED, Table 7 does not present a value regarding the time to initiate a preventive maintenance activity. On the contrary, the more reliable and expensive solutions are identified as ID4 to ID11 in Table 7, and they are marked as × in Figure 9. The inclusion of a redundant Prt. IED is considered for such solutions.

The maximum value for the times to initiate a preventive maintenance activity is 4,380 hours (from Table 1, see TM_{max} values). It can be seen that the times supplied by the algorithms in Table 7 are close to such a value. It shows that the time among preventive maintenance activities is maximised by the optimisers as much as possible.

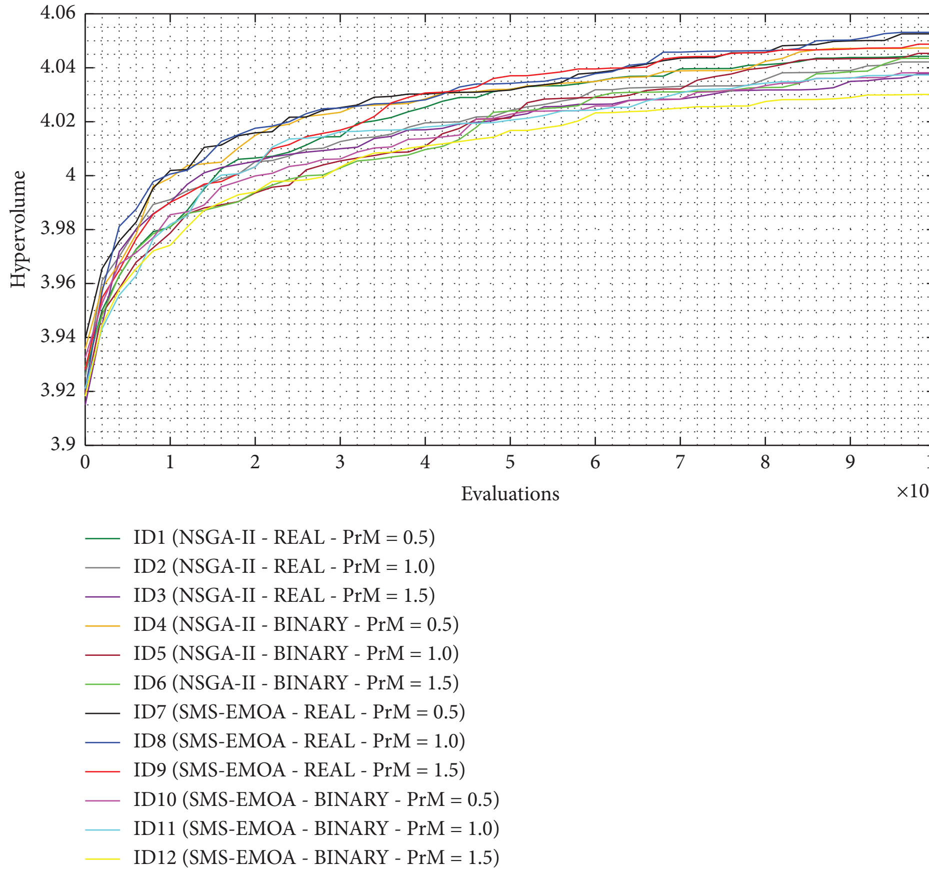

FIGURE 7: Average hypervolume vs. number of evaluations (3-objective problem).

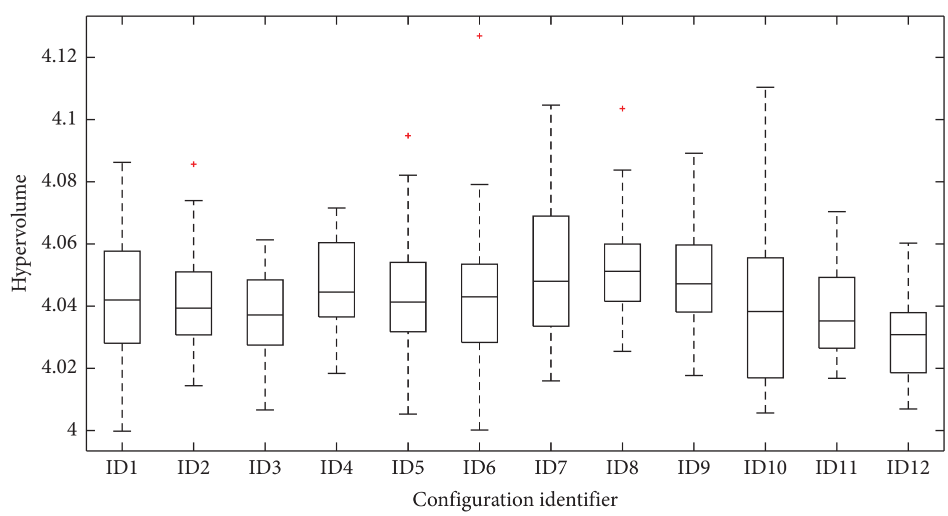

FIGURE 8: Box plots for the achieved hypervolume (3-objective problem, identifiers as in Table 5).

Finally, the accumulated hypervolume for the front of solutions achieves a value of 4.1702, which was computed as described in Ref. [41]. Therefore, this value overcomes the value of 4.1269, which is the maximum value in Table 5.

4.3. Discussion. Previously, the case study was solved from 2- and 3-objective approaches. Both approaches consider unavailability and cost as objective functions. However, the 3-objective approach considers separately the acquisition cost and the operational cost. The robustness of the 2-

Table 6: p values from the Wilcoxon signed-rank test.

Comparison	p value	Conclusion H_0
ID8–ID12	$0.0017 < 0.05$	Rejected
ID8–ID11	$0.0057 < 0.05$	Rejected
ID3–ID8	$0.0117 < 0.05$	Rejected
ID10-ID8	$0.0582 > 0.05$	Not rejected
ID2–ID8	$0.0680 > 0.05$	Not rejected
ID1–ID8	$0.2305 > 0.05$	Not rejected
ID8-ID9	$0.2586 > 0.05$	Not rejected
ID6–ID8	$0.2736 > 0.05$	Not rejected
ID5–ID8	$0.3392 > 0.05$	Not rejected
ID4–ID8	$0.4342 > 0.05$	Not rejected
ID7-ID8	$0.7677 > 0.05$	Not rejected

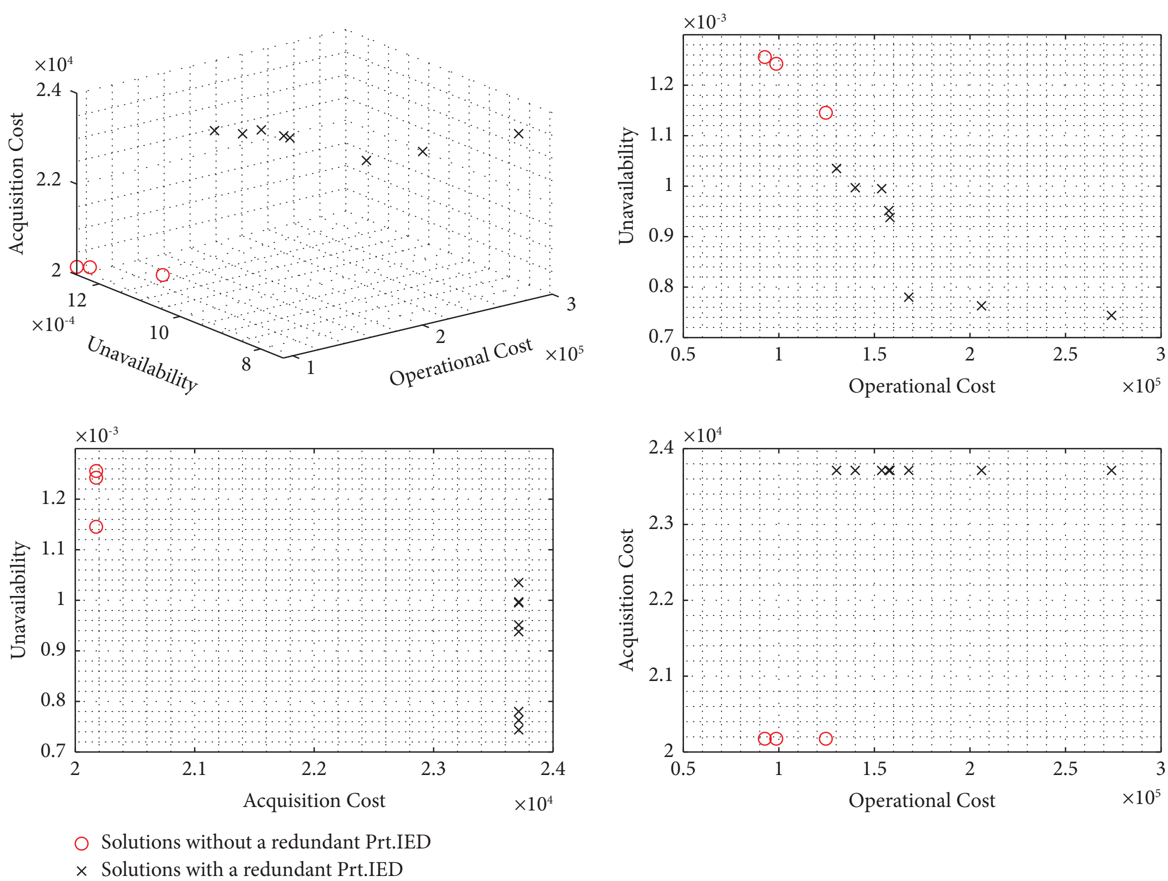

Figure 9: Accumulated nondominated front (3-objective problem).

objective approach is highlighted, since nonsignificant statistical differences were found while several configurations were studied. Nevertheless, it can be seen that the problem is more complex when the 3-objective approach is considered because significant statistical differences were found. Friedman's test brings to light that a better order was reached when real coding and 1 gene per chromosome were used with the SMS-EMOA method. Hence, such a configuration could be recommended to SAS designers.

Table 3 displays the configurations with the best average ranks when two objectives were considered. These are identified as ID2, which uses the NSGA-II method with a mutation probability of 1.0 gene per chromosome (real coding), and ID7, which uses the SMS-EMOA method with 0.5 gene per chromosome (real coding). Moreover, Table 5 (column 10) displays the configurations with the best average ranks when three objectives were considered. These are identified as ID8, which employs the SMS-EMOA method with 1.0 gene per chromosome (real coding), and ID7, which uses the SMS-EMOA with 0.5 gene per chromosome (real coding). In the following subsection, all of them are considered to compare the performance among the approaches used to solve the problem.

Table 7: Optimum solutions obtained for the 3-objective problem.

ID	Q	Operational cost (€)	Acquisition cost (€)	TS (h)	Mu (h)	Cnt. IED (h)	ESW (h)	Prt. IED (h)	Prt. IED (h)
1	0.001256	92,645.00	20,175.00	4,295	3,937	4,270	4,140	4,174	0
2	0.001242	98,637.50	20,175.00	4,302	4,303	4,360	4,355	4,050	0
3	0.001145	124,582.50	20,175.00	4,364	4,225	4,088	4,364	4,378	0
4	0.001035	130,177.50	23,712.50	4,282	4,238	4,294	3,974	4,263	3,989
5	0.000997	139,962.50	23,712.50	4,316	4,358	4,351	4,328	3,953	4,337
6	0.000995	153,815.00	23,712.50	4,380	4,378	4,279	4,227	4,214	4,344
7	0.000951	157,527.50	23,712.50	4,355	4,369	4,234	4,369	4,374	3,726
8	0.000938	158,160.00	23,712.50	4,275	4,275	4,364	4,260	4,364	4,178
9	0.000780	167,982.50	23,712.50	3,758	4,221	4,221	4,365	4,336	4,317
10	0.000763	206,047.50	23,712.50	4,380	4,380	4,380	4,357	4,122	3,537
11	0.000744	274,085.00	23,712.50	4,380	4,380	4,380	4,380	3,946	3,889

Table 8: Statistical analysis for the best average rank configurations from both 2-objective and transformed 3-objective problems.

ID	Objectives	Method	Encoding	Mutation	Average	Median	Maximum	Minimum	Standard deviation	Average rank
1	2	NSGA-II	Real	1.0	3.4495	3.4456	3.4898	3.4141	0.0192	2.5238
2	2	SMS-EMOA	Real	0.5	3.4471	3.4474	3.4800	3.4166	0.0150	2.7142
3	3	SMS-EMOA	Real	1.0	3.4517	3.4513	3.4965	3.4274	0.0166	2.3809
4	3	SMS-EMOA	Real	0.5	3.4513	3.4470	3.4965	3.4191	0.0225	2.3810
p value										0.8150

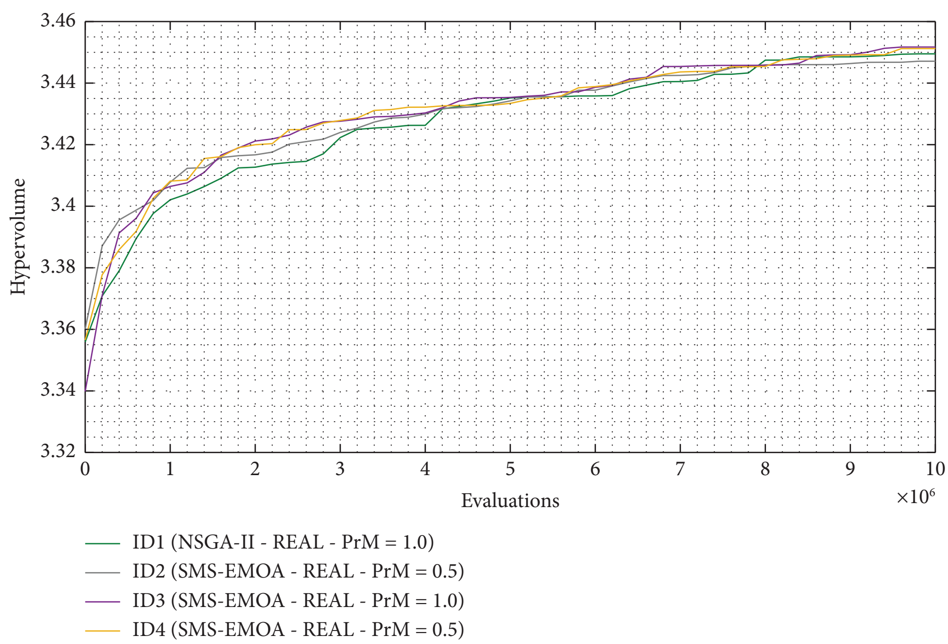

Figure 10: Average hypervolume vs. number of evaluations (comparison between approaches).

4.4. Comparing the Solutions. In order to compare the results of the two approaches, the results of the 3-objective approach must be transformed. Therefore, before computing the hypervolume, the operational cost, and the acquisition cost must be added. In columns 1 to 5 of Table 8, it is displayed the relationship between the configuration identifiers and the methods.

Figure 10 shows the evolution of the average hypervolume values related to the evolution of evaluations. The best average hypervolume value is reached by the

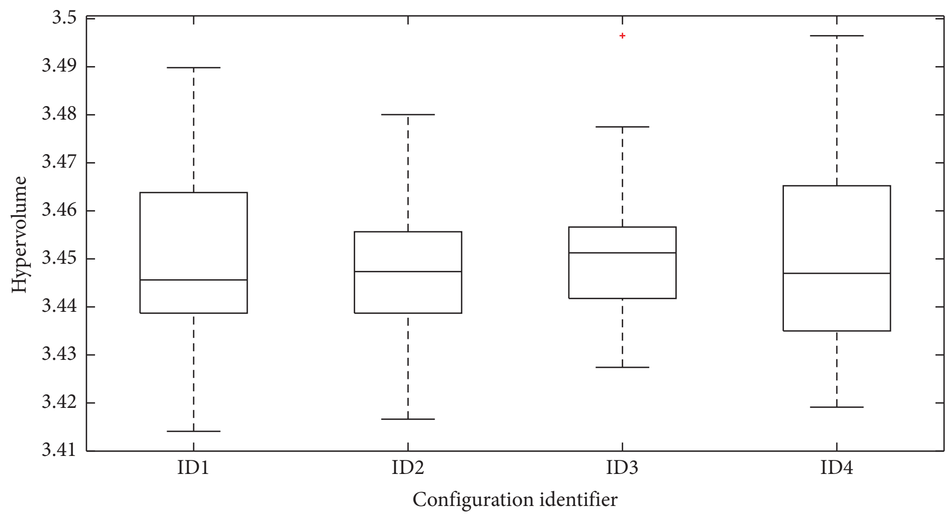

Figure 11: Box plots of the final hypervolume (comparison, identifiers as in Table 8).

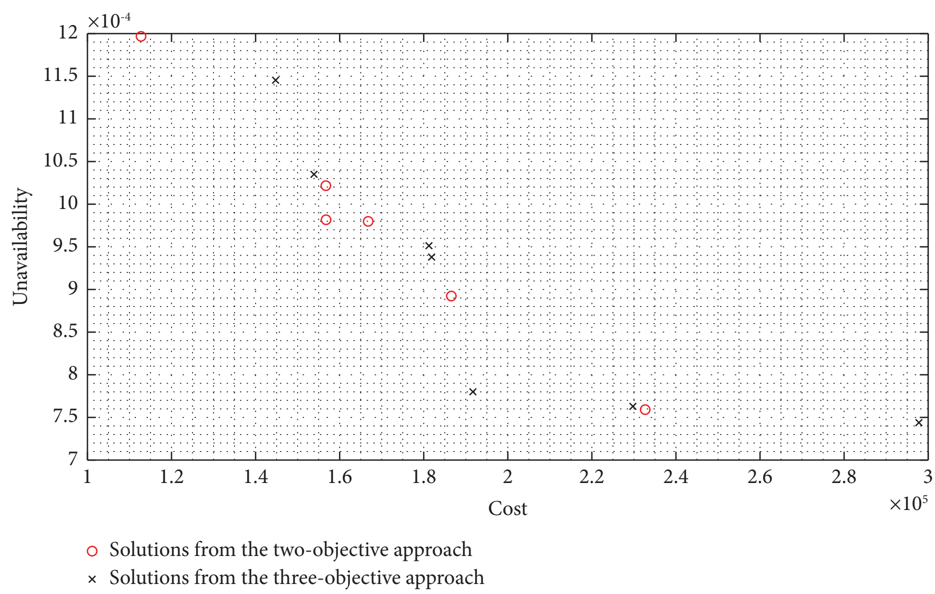

Figure 12: Accumulated nondominated front.

configuration identified as ID3, which uses real coding with the SMS-EMOA and 1.0 gene per chromosome.

In Figure 11, box plots are employed to show the distribution of hypervolume values finally achieved. Table 8 (columns 6 to 10) summarises the statistical information provided by these box plots. The configuration identified as ID3, which employs real coding with the SMS-EMOA method and 1.0 gene per chromosome, achieves the best average, median, minimum, and maximum hypervolume values. Finally, the configuration identified as ID2, which employs real coding with the SMS-EMOA method and 0.5 gene per chromosome, presents the smallest standard deviation value.

Next, it is necessary to check whether one configuration works better than another. Therefore, a hypothesis test of statistical significance is performed. Employing the Friedman's test, the average ranks were computed and ordered. In Table 8 (column 11), such average ranks are shown. The best average rank is supplied by the configuration identified as ID3, which employs real coding with 1.0 gene per chromosome and the SMS-EMOA method. Nevertheless, the obtained p value of 0.8150 does not allow the rejection of H_0 (p value >0.05). Hence, the conclusion "at least the configuration ID3 performs better than some other configuration" cannot be established. However, based on the Friedman test, it can be established that a better order was obtained for the 3-objective approach. SAS designers could therefore be advised to use the multiobjectivisation approach, and in particular, the use of the SMS-EMOA method and real coding.

Figure 12 displays the nondominated solutions. Such solutions were obtained once the whole simulation process was completed from both approaches. Such a figure shows, on the one hand, the solutions marked as O, which were achieved from the 2-objective approach. On the other hand, the solutions marked as × are shown, which were achieved from the 3-objective approach. The accumulated Hypervolume for the solutions front reaches a value of 3.5539. Such a value is higher than 3.4965, which is the maximum value in Table 8.

5. Conclusions

In order to provide a methodology for the reliable architectural design of substation automation systems (SAS), multiobjective evolutionary algorithms, and discrete event simulation are combined. The joint optimisation of design and maintenance strategy is considered by using such a methodology. Both corrective and preventive maintenance are contemplated in the maintenance strategy. Regarding preventive maintenance, the main target consists of deciding the periodic time to initiate such activities. The conflict between cost and availability is addressed when both acquisition and operational costs are managed. A population of individuals is evolved by the multiobjective evolutionary algorithm until it reaches the stopping criterion. Each individual denotes a feasible design and preventive maintenance strategy for the system. Discrete event simulation is then employed to emulate the behaviour of the system and evaluate the objective functions. A case study is developed in which two multiobjective approaches are studied: on the one hand, a 2-objective approach that considers both availability and cost as objectives, and on the other hand, a 3-objective approach that considers availability and cost as objectives again. Nevertheless, in this second approach, the cost is decomposed between operational and acquisition cost such a procedure is termed multiobjectivisation. Availability-cost-balanced solutions are provided when the methodology is applied. A thorough hypothesis test is conducted in order to find out which approach is the most appropriate.

The case study consists of a section of a subsystem, which is included in SAS. It is a bay line of a single bus of a small transmission substation, which is employed to transform energy (220 kV. $\longrightarrow$ 132 kV). In this case, two state-of-the-art multiobjective evolutionary algorithms are employed to compare their performances: The S-metric selection evolutionary multiobjective optimisation algorithm (SMS-EMOA) and the nondominated sorting genetic algorithm II (NSGA-II).

Both approaches produced a collection of nondominated solutions. When the 2-objective approach was employed, all configurations worked analogously. Nevertheless, when the 3-objectives approach was considered, significant differences were found. It can be concluded that the complexity of the problem is greater when the multiobjectivisation approach is considered.

After conducting the Friedman´s test, a pairwise comparison was carried out for the best-ordered configurations from both approaches. As a result, the 3-objective approach were firstly ordered. Therefore, the multiobjectivisation approach showed a positive effect. Furthermore, the method based on the hypervolume indicator (SMS-EMOA) with real coding performed better than the method based on Pareto dominance (NSGA-II). Thus, it could be recommended to use the multiobjectivisation approach and the SMS-EMOA method to obtain a set of availability-cost balanced solutions. Considering unavailability-cost constraints, the decision makers can select the desirable solution from such a set of solutions.

In the future, it is proposed to extend the analysis to more complex architectures to test the multiobjectivisation effect when more complex designs are considered.

Data Availability

The data that support the findings of this study are available from the corresponding authors upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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