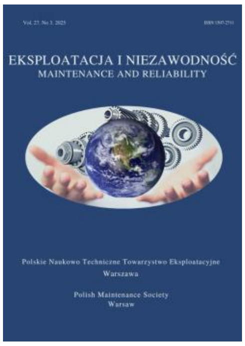

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Reliability-oriented twin model for integrating offshore wind farm maintenance activities

Indexed by: Web of Science Group

Yorlandys Salgado Duarte[a,*], Janusz Szpytko[a]

[a] Faculty of Mechanical Engineering and Robotics, AGH University of Krakow, Poland

Highlights

- Optimizes a probabilistic indicator.
- Probabilistic-focused twin model that addresses uncertainties and enumeration.
- Demonstrates feasible heuristic optimization algorithms.

Abstract

In the context of Power Systems, scheduling maintenance activities is a recognized Non-deterministic Polynomial-Time (NP) hard optimization problem. This complexity stems from the dynamic nature of Power Systems and the varied conditions within them. When wind energy is integrated into the system through offshore wind farms and is composed of a large volume of small units, the challenges become even more remarkable due to the uncertainties introduced by wind variability and the need to coordinate a high volume of maintenance activities. This paper tackles this complex optimization issue using a probabilistic-focused twin model that addresses uncertainties and enumeration with scenario analysis based on simulations. The proposed solution quantifies and optimizes a probabilistic indicator estimated using the Monte Carlo method, and demonstrates feasible heuristic optimization algorithms that balance computation time and accuracy. IEEE-RTS is used to benchmark the proposed solution and to discriminate the best feasible heuristic optimization algorithm.

Keywords

reliability, maintenance, Markow chain Monte Carlo simulations, heuristic optimization, power systems, offshore wind farms.

1. Introduction

There is interest, especially in Europe, to increase wind energy capacity to meet the 2030 Climate and Energy goals. Reports on the area [12] show 255 GW of wind capacity, 225 GW onshore and 30 GW offshore. Studies and research also search to see where the perspective is heading, and among green energy alternatives, wind farms (onshore and then offshore) appear to be the focus from a capacity point of view [6]. Specifically, the nature of wind is fundamental to achieving the desired result, and studies in the area evaluate the potential of Europe from this perspective [17]. In Europe, the need to introduce wind energy aligns with climate change and becomes more relevant every day [13]. However, the increasing integration of these renewable energy sources, particularly offshore wind farms, into Power Systems, has introduced new complexities in operation, management, and maintenance. Offshore wind farms consist of numerous small generating units spread across oceanic areas, each subject to the stochastic nature of wind conditions. This variability introduces significant uncertainties, complicating the already challenging task of scheduling maintenance activities, which, in addition, must be coordinated

(*) Corresponding author.
E-mail addresses: Y. Salgado Duarte (ORCID: 0000-0002-5085-3170) salgado@agh.edu.pl, J. Szpytko (ORCID: 0000-0001-7064-0183) szpytko@agh.edu.pl,

with the interconnected Power System. Furthermore, given oceanic environmental conditions, wind turbine generators suffer from accelerated degradation, making it relevant to introduce the reliability of their operating performance [11] in the design of the maintenance schedule.

Maintenance scheduling in Power Systems is recognized as a nondeterministic polynomial-time (NP) hard optimization problem. The complexity of this problem arises from the dynamic nature of Power Systems, the need to maintain a balance between supply and demand, and the requirement to ensure system reliability amidst varying operational conditions. When wind energy is incorporated, these challenges increase due to the unpredictable nature of the wind and the need to coordinate many maintenance tasks for all individual units in a precise manner.

In response to these challenges, this paper presents a reliability-oriented twin model designed to optimize maintenance scheduling for offshore wind farms integrated into a Power System. The model employs a probabilistic approach, using Monte Carlo simulations to estimate a continuous probability distribution function. This function is used to quantify and optimize a probabilistic indicator, specifically the well-defined expected-energy-not-supplied (EENS). The Monte Carlo method allows for the aggregation of multiple uncertainties and provides a clear, measurable target for optimization. In this paper, we contribute with a solution, where the probabilistic approach is essential to optimize the underlying modeled process. Within the reliability field, there are well-established standard methodologies; however, not all are recycled in the probabilistic model proposed in this contribution. Specifically, in our proposed solution, we use the Reliability Block Diagram (RBD) model [20] to address the Power System's functional structure, composed of many generator units, and the Markov model [30] to simulate the stochastic transitions between failures and repair times of each component considered in the system, which at the same time is convoluted with the planning maintenance process to recreate all the potential states of the element modeled. This organic connection allows for the simulation and coordination of planned and unexpected events.

The probabilistic approach proposed to solve the underlined optimization problem has weaknesses from the optimization perspective. Since we estimate a risk indicator (EENS) via the Monte Carlo method, the function to be optimized ends as a black box, where the optimization algorithm manages the inputs and outputs, but the functional relationship inside is not an explicit equation. This condition forces us to discard traditional optimization algorithms and use heuristics. As we know, heuristics do not provide a guarantee of finding a global minimum. However, there is an extensive family of heuristic optimization algorithms that increase in applicability and improve precision [8], and it is a usual practice to test more than one algorithm for a specific problem. Furthermore, when the optimization problem is well known, specific heuristics are designed to solve it [26].

The design of heuristics to solve specific problems and the benchmark between them is a common practice [27] and [28]. When complexity and singularities merge into a unique problem, optimization algorithms must be adapted to address the interactions of several layers to be optimized, leaving open the conclusion of which algorithm is the best to be used. The comparison between heuristic strategies is usually addressed with metrics. Mainly using the best, worst, mean, and standard deviation [7]. Certainly, for the same scenario to be evaluated, the same conditions must be met.

In our case, the proposed model integrates advanced heuristic optimization algorithms to balance computation time and accuracy, ensuring the delivery of reliable performance within given scenarios. These algorithms [23], including Particle Swarm Optimization (PSO), Nonuniform Pattern Search (NUPS), Surrogate Optimization, and Genetic Algorithm (GA), are evaluated for their effectiveness in minimizing the EENS, demonstrating their applicability to the complex optimization landscape of Power Systems maintenance. We decided to benchmark these algorithms using the best evaluation as the metric to select the most appropriate option to solve the underline optimization problem.

Furthermore, even when we focus specifically in this paper on the optimization module, the model introduces and incorporates a digital twin framework, enhancing real-time monitoring and performance optimization by creating virtual representations of physical assets. This practice has recently been applied to the maintenance modeling process [29]. This point is briefly described in the architecture of the solution. This framework enables continuous updates of system status, optimizing maintenance schedules based on current conditions and historical data. By focusing on the probabilistic modeling and simulation aspects, this study lays the groundwork for future research to refine model parameters and explore additional optimization algorithms.

Specifically, twin models are widely applied for maintenance purposes in various industries. Maintenance-focused digital twins create virtual representations of physical assets, such as machinery, equipment, or infrastructure, to monitor their condition, analyze performance, and optimize maintenance activities. Using digital twins for maintenance offers several benefits, including increased efficiency, reduced downtime, system resilience, and improved asset reliability.

Among many areas of application in the field, in our proposal, we use the data generated from the system's operation to continuously update the system's status by calibrating all the model parameters and variables time-dependent every time a scenario is loaded. Certainly, the system becomes more resilient because the virtual counterpart model reflects the status of the modeled physical system. Essentially, we elaborate and apply Condition Monitoring [4]. In addition, we also use Performance Optimization [10], where maintenance teams (technology users) can identify ways to optimize asset performance and efficiency by simulating different operating conditions and scenarios on the digital twin. These simulations allow them to experiment with varying maintenance strategies and assess the impact on asset reliability, availability, and productivity. This point is crucial in our proposed solution. We are modeling an existing process, so using scenarios of potential maintenance outcomes and the historical data related to the system operation, we optimize the process using a holistic probabilistic indicator, which integrates through a convolution product, the system functional capacity, and the system functional requirements.

The application of digital twins for maintenance is attracting attention in all industries, including Manufacturing [16], Aerospace [25], Transportation [5], and Energy [24]. As technology advances and data integration becomes seamless, the use of digital twins for maintenance purposes is expected to become even more prevalent, transforming how maintenance is performed and enhancing overall asset management strategies. In our proposed idea, we improve the use of Data-Driven Reliability (DDR) [15] to calibrate the parameters and variables of the model, keeping them up-to-date and improving the system's resilience. Usually, almost all model parameters and variables depend on data in a specific period (time-dependent), so merging the online connection through technology integration and implementing comprehensive logical decision-making flow diagrams with the help of Machine Learning (ML) makes it possible to address model self-calibration.

The validation of the proposed model is conducted using the IEEE Reliability Test System (IEEE-RTS) described in [9], ensuring its accuracy and applicability. Counting with a test system, allows us to benchmark the features of the proposed model. Within the literature consulted on this matter, shown in Table 1, the preference in approach appears to be risk-oriented, since the reference using a cost-oriented approach at the end applies risk constraints. In the case of methods, since we aim to apply this solution in real Power Systems, the Monte Carlo simulation method seems to be the best choice from the scalability point of view, allowing also the hourly resolution window that better represents the system load requirements. The proposal presented here is in line with the trends and in addition offers error control accuracy and ingest the maintenance dispersion scenario, a set of wind farms in this case, and potentially can be adaptable to consider other green sources of energy. In this paper, various scenarios are assessed, including the dispersion of maintenance activities and the integration of offshore wind farms, showcasing the model's adaptability to different conditions. The introduction of dispersed maintenance activities reflects a more realistic representation of actual operations, while the integration of offshore wind farms highlights the model's capability to enhance system resilience and reliability.

Table 1. Maintenance Scheduling solutions for IEEE-RTS.

Dimensions								
Reference	Approach	Algorithm	Methods	Resolution window	Error Control	Scalability	Maintenance dispersion	Wind Farms
[3]	Risk	Recursive technique	Risk leveling technique	Weekly	Uncertain, the enumeration is truncated	Hard, based on enumeration	No	No
[18]	Risk	Dynamic Programming Optimization Algorithm	Risk leveling technique	Weekly	Uncertain, the enumeration is truncated	Hard, based on enumeration	No	No
[19]	Mainly cost, with risk constraints	Genetic Algorithm (GA)	Monte Carlo simulation	Weekly	Fix sample	Easy	No	No
[21]	Risk	Particle Swarn Optimization (PSO) and Genetic Algorithm (GA)	Monte Carlo simulation	Hourly	Fix sample	Easy	No	No
This proposal	Risk	Particle Swarm Optimization (PSO), Nonuniform Pattern Search (NUPS), Surrogate Optimization, and Genetic Algorithm (GA)	Monte Carlo simulation	Hourly	Less than 5%	Easy	Yes	Yes

Once we have introduced all dimensions of the discussion, we can state that reliability-oriented twin models can be used to integrate offshore wind farm maintenance activities, and the remaining sections of the paper are as follows. First, the section Materials and Methods conceptualizes and formalizes the proposed model. Here, we list indices, parameters, and variables, we show the architecture of the solution, and we define the pseudo-logic of the Monte Carlo method and its connection with the optimization problem. Then, in the section Results and Discussion, we introduce the parameterization used as a starting point for validation, and then we change the base scenario to reflect the objectives of this research, aiming to challenge the applicability of the proposed solution. Finally, the section Conclusions summarizes the efforts of this contribution and future work.

2. Materials and Methods

This section describes the probabilistic-oriented optimization model to coordinate maintenance activities scheduling. Here, we present the conceptualization and definition of the model of each index, parameter, and variable. The model aims to minimize a probabilistic indicator defined as the expected value $E[Z]$ of a probability distribution estimated using the Monte Carlo method. We list below all indexes, parameters, and variables, followed by the conceptualization, which includes mainly the architecture diagram illustrating the connections between different model layers, and then the formalization, with the pseudo-logic algorithm proposed to address the maintenance scheduling optimization problem.

Indices

i index of the generator unit

t index of time

k index of maintenance or failures

m, n sub-indexes to denote variation

N index of simulation

S index of iteration in the optimization algorithm

Parameters

β error criterion

T simulation time window

N_{RNi} number of random numbers generated in the i-th generator unit

N_{MTi} number of maintenance in the i-th generator unit

$\overline{C}_i$ nominal generator unit capacity

$MTTF_i$ Mean-Time-To-Failure in the i-th generator unit

$MTTR_i$ Mean-Time-To-Repair in the i-th generator unit

$M_{i,k}$ k-th Time-To-Maintenance of the i-th generator unit

$D_{i,k}$ k-th Time-Duration-Maintenance of the i-th generator unit

Variables

$\tilde{F}_{i,k}$ k-th random Time-To-Failure in the i-th generator unit

$\tilde{R}_{i,k}$ k-th random Time-To-Repair in the i-th generator unit

$M_{i,1}$ the start times for the first maintenance of the i-th generator unit

C_i stochastic capacity in the i-th generator unit

z_N risk estimation (Energy-Not-Supplied) at the simulation N

X stochastic capacity of the generator unit system

Y forecasted system load

Z risk probability distribution function

$E[Z]$ conditional expected value (Expected-Energy-Not-Supplied) of the Z probability distribution function

$V[Z]$ variance of the Z probability distribution function

Conceptualization: Architecture Diagram to Solve the Optimization Problem

In this paper, we focus on addressing complex and dynamic scheduling challenges of maintenance activities inherent in Power Systems, particularly when integrating wind energy sources using offshore wind farms and consequently managing large volumes of activities in a precise manner. Since we recognize the inherent complexity of scheduling maintenance activities within Power Systems (NP-hard optimization problem), we handle and approach the complexity using probabilistic-oriented assessment and the Monte Carlo method. The use of the Monte Carlo method to estimate the continuous probability distribution function and consequently the probabilistic indicator $E[Z]$, which is the corresponding expected value, allows the aggregation of multiple uncertainties and probabilistic complexity into a single and quantifiable probabilistic metric that can be optimized, offering a clear and measurable target. Also, the proposed solution involves heuristic optimization, since we address the problem with Monte Carlo simulations. In other words, the measurable target to be used as an optimization reference is the result of a simulation.

This paper includes a demonstration of the feasibility of the solution and its performance in given scenarios. This step is critical to validating the applicability of the solution in real-world settings and ensuring reliable results within operational constraints. This approach is illustrated in Figure 1, where the functional connections described in the modeling stage are shown.

In addition, to understand how the Monte Carlo method is applied, Figure 2 illustrates the logic flow of the simulation, which is a reshaped view of Figure 1. The process of estimating the best maintenance scheduling is simple, and only two conditional statements are implemented. The first condition aims to guarantee the accuracy of the estimation of the probability indicator $E[Z]$ by setting a convergence error for each scenario, in this case, a 5% tolerance error. Then, the second conditional statement is related to optimization algorithm convergence, where the process of optimization ends when the difference between consecutive evaluations in the objective function is less than 1.0E-06.

As we can see, the simulation of each potential scenario to be evaluated is independent. Given this singularity, the optimization algorithm can also propose independent maintenance schedules to be implemented. That said, using parallel computing is a feature to be explored, and in our case, we use this property to speed up the estimation of the solution. Figures 1 and 2 illustrate this feature in the connection between the optimization algorithm and the objective function.

Once the starting point of the $M_{i,1}$ maintenance scheduling chain is known, a simulation is built to estimate the risk indicator $E[Z]$ from a probability distribution estimated via the Monte Carlo method. This indicator is used to discriminate the best maintenance scheduling, since all the other parameters and variables in the scenario remain unchanged, and the only variable changing is the starting point of the scheduling chain under the constraints of the scenario. Knowing that we use a simulation approach, to always have comparable simulations, the pseudo-random seed generator is controlled. In this implementation, the Mersenne Twister random generator is used and restarted at the initial stage of the simulation, ensuring the uniform reproducibility of the results.

In the following conceptualization section, a detailed description of the simulation is illustrated and formalized.

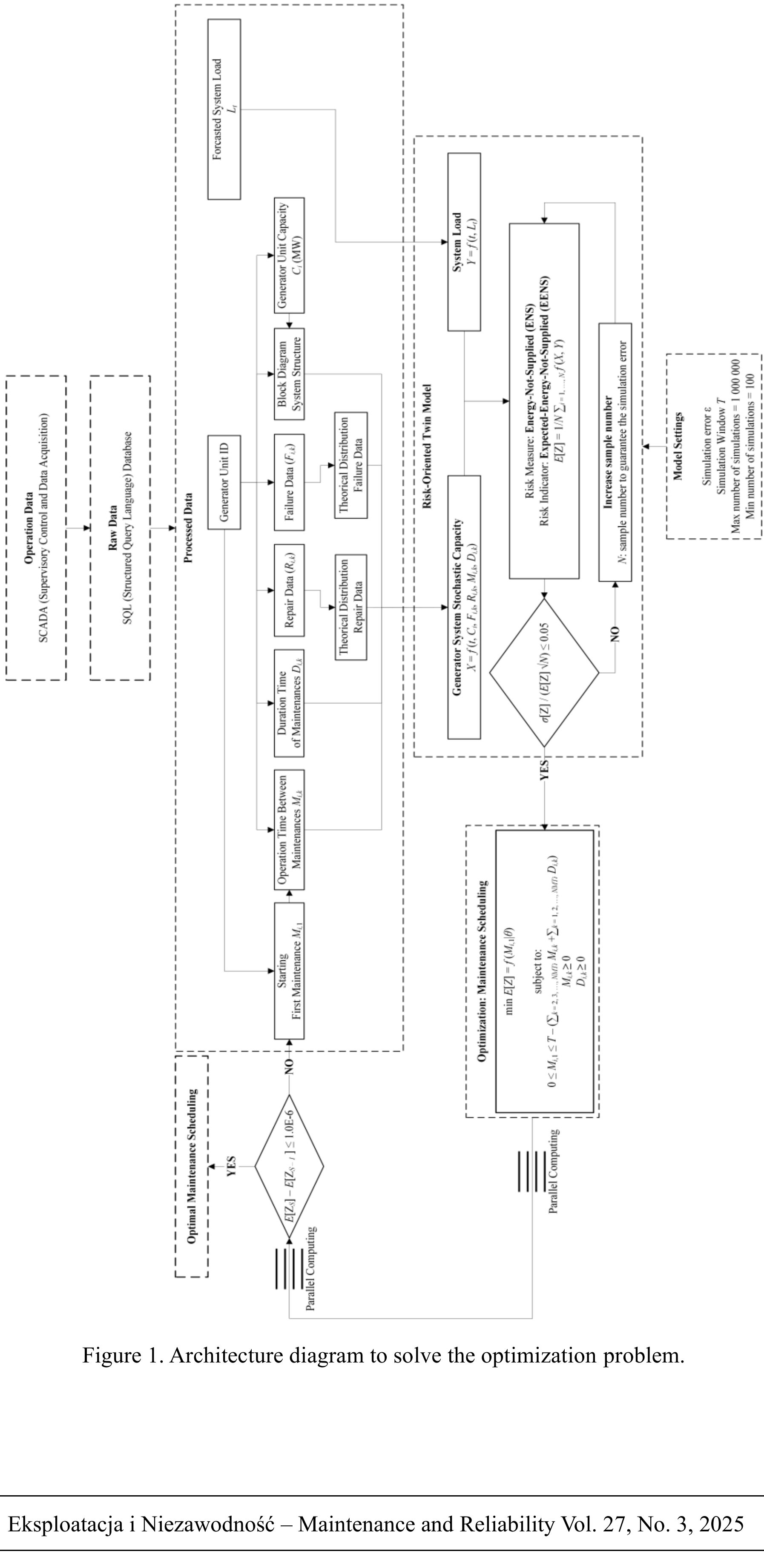

Figure 1. Architecture diagram to solve the optimization problem.

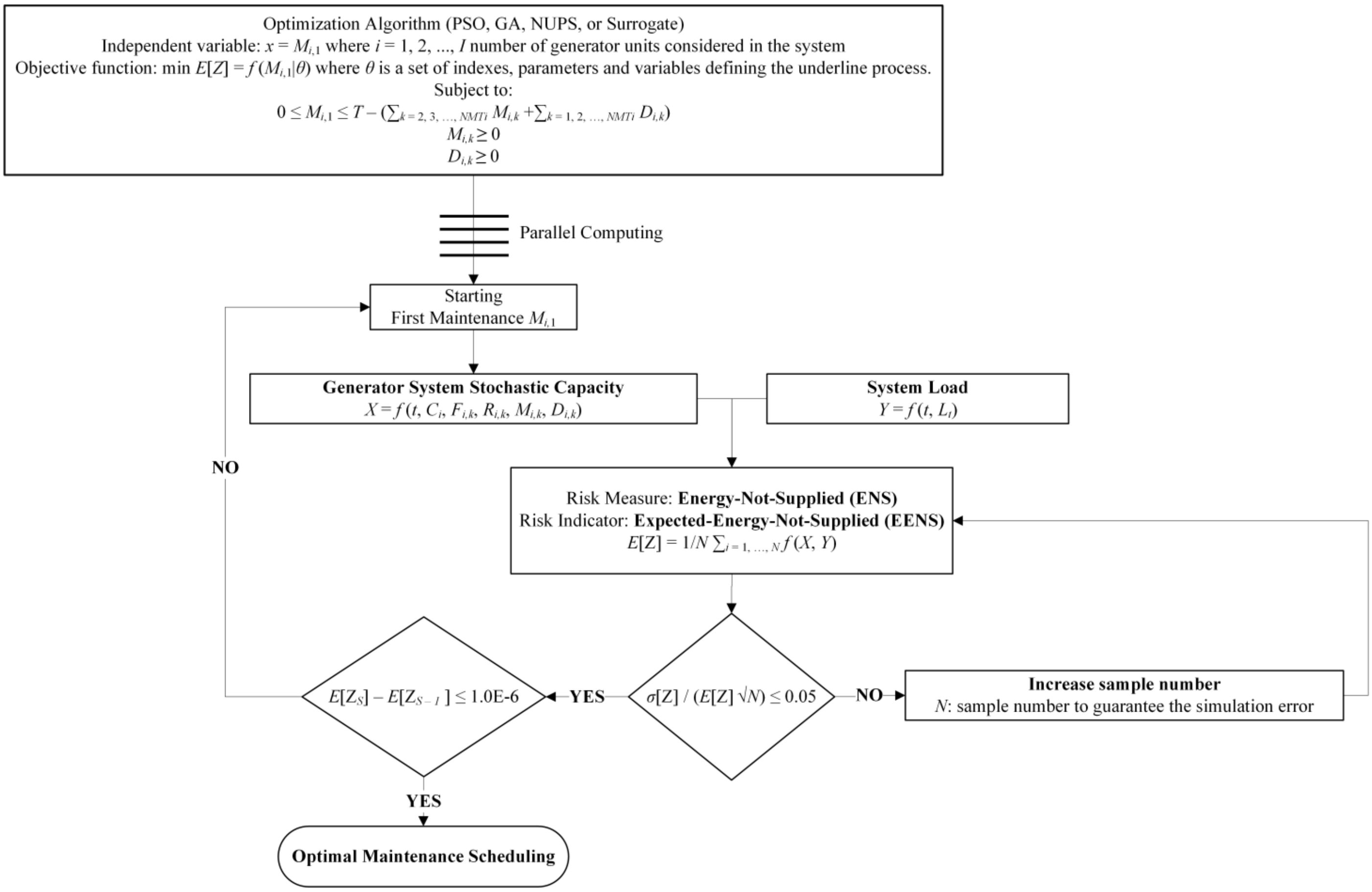

Figure 2. Flow diagram to solve the optimization problem.

Formalization: Maintenance scheduling optimization problem modeling

I. Knowing the definition (1) of the optimization problem.

$$min \quad E[Z] = f(M_{i,1}|\theta)$$

subject to:

$$0 \le M_{i,1} \le T - \left(\sum_{k=2}^{N_{MT_i}} M_{i,k} + \sum_{k=1}^{N_{MT_i}} D_{i,k}\right) \quad M_{i,k} \ge 0 \quad D_{i,k} \ge 0 \tag{1}$$

where:

Z is a conditional random variable, defined in (2), and it is the convolution product of probability distribution functions X and Y.

$$Z = \begin{cases} \sum_{t=1}^{T} Y_t - X_t & \text{if} \quad X_t < Y_t \\ 0 & \text{if} \quad X_t \ge Y_t \end{cases} \tag{2}$$

X is the capacity of the stochastic generation unit system, defined in (3), and it is defined as a probability distribution function.

$$X = {}_{i=1}^{I}(||)C_i \tag{3}$$

Y is the forecast system load and is defined as a probability distribution function. The system load is the result of a forecast model, either weekly, daily, or hourly resolution.

$E[Z]$ is the conditional expected value of the Z probability distribution function and the optimization target.

$M_{i,1}$ is the start time for the first maintenance of the i-th generator unit.

θ is a set of indexes, parameters, and variables defined later coherently in this section.

T is the simulation time window.

$M_{i,k}$ is the k-th Time-To-Maintenance of the i-th generator unit, representing the moment in the simulation window when a maintenance activity k will be conducted in the generator unit i.

$D_{i,k}$ is the k-th Time-Duration-Maintenance of the i-th generator unit, representing the duration time of the maintenance activity k in the generator unit i.

N_{MTi} is the number of maintenance in the i-th generator unit.

k is the index of maintenance.

Note that in the context of Power Systems, if X and Y are expressed in Megawatts (MW), t is expressed in hours (h), and T is a (one-year) time horizon, then Z represents the expected energy not supplied over one year due to the unavailability of the generation unit system to supply the system load and is expressed in (MWh/year).

II. An heuristic optimization algorithm proposes a set of x_i =

$M_{i,1}$ starting maintenance time for each generator unit considered in the system, given the constraints of the simulation window defined in (4).

$$0 \leq M_{i,1} \leq T - \left(\sum_{k=2}^{N_{MT_i}} M_{i,k} + \sum_{k=1}^{N_{MT_i}} D_{i,k}\right) \tag{4}$$

Then N Monte Carlo simulations are computed to estimate N conditional random values (z_1, z_2, …, z_N), in this context, Energy-Not-Supplied (ENS), as follows.

A. N values of ENS (z_1, z_2, …, z_N) are determined as a convolution product between X and Y, given the set of $M_{i,1}$ provided by the optimization algorithm and completing the $M_{i,k}$ chain for each generator unit, where X is the stochastic capacity of the generator unit system, and Y is the forecasted system load. The convolution product Z is achieved as follows.

1. For N values of ENS (z_1, z_2, …, z_N) computed by Monte Carlo simulations,

a. First, the capacity distribution function of the generator unit system X is computed as follows:

i. For each generator unit i,

(1). Given the simulation window T constraint, k-th independent random numbers are simulated sequentially $\tilde{F}_{i,k}$ and $\tilde{R}_{i,k}$, from probability distribution functions that simulate the most likely degradation process, i.e., concatenations of Time-To-Failure and Time-To-Repair random values. In this paper, since we use data from the IEEE Reliability Test System (RTS) described in [9] to validate the implementation of the optimization algorithm, only exponential distributions are used. This sequential simulation and then concatenation is conducted until the constraint (5) is achieved.

$$\sum_{k=1}^{m} \tilde{F}_{i,k} + \sum_{k=1}^{m} \tilde{R}_{i,k} \geq T \tag{5}$$

Knowing that $m = 1, \ldots, N_{RNi}$, which is the number of random numbers generated. Note that N_{RNi} is a dynamic number because each i-th generator unit may differ. Since we use the Monte Carlo method, the variables $\tilde{F}$ and $\tilde{R}$ are randomly generated $\tilde{F} = \{f_1, f_2, \ldots, f_k\}$, $\tilde{R} = \{r_1, r_2, \ldots, r_k\}$ from the probability distribution describing the underlying phenomenon, where f_k and r_k represent the values in each sequence generated randomly. Usually, exponential distributions when only historical mean values are known. However, if the historical degradation data due to the operation are available, the usual process is to fit a set of probability distributions and assess which one is more closely related to the data by applying Maximum Likelihood Estimation (MLE) and Bayesian Information Criterion (BIC).

(2). Then apply the following function defined in (6),

$$C_i^D(t|\theta) = \begin{cases} \overline{C_i} & \text{if} \quad t < \sum_{k=1}^{m} \tilde{F}_{i,k} + \sum_{k=1}^{m-1} \tilde{R}_{i,k} \\ 0 & \text{if} \quad \sum_{k=1}^{m} \tilde{F}_{i,k} + \sum_{k=1}^{m-1} \tilde{R}_{i,k} \leq t < \sum_{k=1}^{m} \tilde{F}_{i,k} + \sum_{k=1}^{m} \tilde{R}_{i,k} \end{cases} \tag{6}$$

which is a simulated stochastic or probabilistic vector $C^D{}_i$ that describes the most likely degradation process due to the operation (the superscript D denotes the degradation component contribution), where t is the time, and θ is the set of variables and parameters of the function. Specifically, $\overline{C_i}$ is the nominal capacity of the generator unit (which is an operational parameter related to the generator unit), $\tilde{F}_{i,k}$ is the k-th random Time-To-Failure sequence in the i-th generator unit, and $\tilde{R}_{i,k}$ is the k-th random Time-To-Repair sequence in the i-th generator unit. Note that, F is the Time-To-Failure, a random variable representing the unexpected failures k associated with component degradation due to system operation in the generator unit i, and R is the Time-To-Repair, a random variable representing the magnitude of the failure k, translated on duration time, which also represents the expertise of the workers who repair the failure, and the logistics behind it, in the generator unit i.

(a). In this paper, we consider a wide range of generator unit types. Precisely, Oil/Stream, Oil/CT, Hydro, Nuclear, and Wind. All types of generator units, in addition to wind turbines, have a constant nominal capacity $\overline{C_i}$, i.e., the primary source of energy is always assumed to be available. Therefore, in the case of wind energy, knowing that the primary source of energy is the wind, first is necessary to simulate the wind and then using the characteristic function of the wind turbine, translate the wind speed into energy. In our case, we simulate the most likely wind speed v with a Weibull model [1], defined in (7),

$$f(v) = \frac{\beta}{\delta}\left(\frac{v}{\delta}\right)^{\beta-1} exp\left[-\left(\frac{v}{\delta}\right)^{\beta}\right] \tag{7}$$

estimating the shape (8) and scale (9) parameters of the probability distribution function with the mean and standard deviation of the historical wind μ_{sw} and σ_{sw}.

$$\beta = \left(\frac{\sigma_{SW}}{\mu_{SW}}\right)^{-1.086} \tag{8}$$

$$\delta = \frac{\mu_{SW}}{\Gamma(1+\frac{1}{k})} \tag{9}$$

Once the Weibull distribution is parameterized, with the inverse cumulative distribution function defined in (10),

$$F(v) = 1 - e^{\left[-\left(\frac{v}{\delta}\right)^{\beta}\right]} \tag{10}$$

it is possible to simulate v wind values by generating uniform random numbers u with (11),

$$v = \delta(-\ln(u))^{1/\beta} \tag{11}$$

As we can see, the number of random numbers u to be generated depends on t = 1, 2, … T, which is the simulation window.

Then, the power capacity of each wind turbine is estimated with the following model [14], defined in (12).

$$P(v) = \begin{cases} 0 & \text{if} \quad 0 \le v < v_{ci} \\ (A + B \times (v) + C \times (v)^2) \times P_r & \text{if} \quad v_{ci} \le v < v_r \\ P_r & \text{if} \quad v_r \le v < v_{co} \\ 0 & \text{if} \quad v \ge v_{co} \end{cases} \tag{12}$$

where P_r, v_{ci}, v_r, and v_{co} are nominal output power, wind speed necessary for start-up, wind speed corresponding to the wind turbine nominal power, and cutting wind speed per wind turbine safety reasons respectively. The constants A, B, and C depend on v_{ci}, v_r and v_{co} and are defined in (13).

$$A = \frac{1}{(v_{ci} - v_r)^2}\left\{v_{ci}(v_{ci} + v_r) - 4v_{ci}v_r\left[\frac{v_{ci} + v_r}{2v_r}\right]^3\right\}$$

$$B = \frac{1}{(v_{ci} - v_r)^2}\left\{4(v_{ci} + v_r)\left[\frac{v_{ci} + v_r}{2v_r}\right]^3 - (3v_{ci} + v_r)\right\}$$

$$C = \frac{1}{(v_{ci}-v_r)^2}\left\{2 - 4\left[\frac{v_{ci}+v_r}{2v_r}\right]^3\right\} \tag{13}$$

Consequently, for wind turbines, the parameter $\overline{C_i}$ defined in (6), is replaced by the variable $P_i(v)$, which represents the power wind capacity of the i-th generator unit (specifically, wind turbine).

(3). Following the same process, but now considering maintenance scheduling activities, given the chain of $M_{i,k}$ and $D_{i,k}$ and applying the definition (14), we estimate a deterministic vector C^M_i that describes the maintenance lifecycle for each component considered (the superscript M denotes the maintenance component contribution), where n = 1, …, N_{MTi} is the number of maintenance activities, and also is a dynamic number for each generator unit i.

$$C_i^M(t|\theta) = \begin{cases} \overline{C_i} & \text{if} \quad t < \sum_{k=1}^{n} M_{i,k} + \sum_{k=1}^{n-1} D_{i,k} \\ 0 & \text{if} \quad \sum_{k=1}^{n} M_{i,k} + \sum_{k=1}^{n-1} D_{i,k} \le t < \sum_{k=1}^{n} M_{i,k} + \sum_{k=1}^{n} D_{i,k} \end{cases} \tag{14}$$

(4). Combining both processes $C_i = C^D_i$ & C^M_i, (junction symbol & refers to AND logic) the stochastic capacity due to the operation considering the scheduling maintenance activities is achieved, which is a vector that overlaps the contribution of the degradation and maintenance components.

ii. Then, knowing that all generator units are in parallel and the given independent C_i vector for each generator unit i (Oil/Stream, Oil/CT, Hydro, Nuclear, and Wind), by aggregating all generator units using the junction symbol || (junction symbol || refers to OR logic), the capacity of the generator unit system X is obtained applying the notation (15).

$$X = {}_{i=1}^{I}(||)C_i \tag{15}$$

where I is the number of generator units considered in the system.

b. Second, the system load Y is estimated. Usually, the system load is the result of a forecast model, either daily or hourly, and typically addressed using Auto-Regressive Integrated Moving Average (ARIMA) regression models. However, in this contribution, since we need to validate the applicability of the optimization problem, the Hourly Load Duration Curve (LDC) is sourced as well from the reference IEEE RTS [9].

c. Taking both vectors X and Y and applying the convolution defined in (2), it is possible to estimate the conditional value of ENS, where t = 1, …, T. Since t is expressed in hours (h), C_i, and consequently X and Y are expressed in Megawatts (MW), and T is usually (one-year), then the value of ENS is expressed in (MWh/year). In this context, Z measures the Energy-Not-Supplied (ENS) in the simulated window.

2. Since we estimate the probability distribution function Z using the Monte Carlo method, then the sequence, (Step 1.) up to this point, is repeated until the conditional expected value $E[Z]$ has an error less than β (0.05 in our case), which is determined as follows,

$$E[Z] \pm \beta E[Z] = E[Z] \pm \frac{\sigma[Z]}{E[Z]\cdot\sqrt{N}} E[Z] = E[Z] \pm \frac{\sigma[Z]}{\sqrt{N}} \tag{16}$$

where the convergence depends on the standard deviation of the estimated ENS values and the square root number of Monte Carlo simulations N performed.

3. The conditional expected value $E[Z]$ is the estimated probabilistic indicator once the desired error is achieved. In this context, Expected-Energy-Not-Supplied (EENS).

4. End of the Monte Carlo simulation method.

B. In each iteration of the optimization algorithm, for the updated values of the estimated ENS until z_N, for $N \neq 1$, the mean $E[Z]$ and variance $V[Z]$ are determined from the sample generated, and the error criterion β is checked. If the desired error is not achieved (in our case, 0.05), N is increased and the Monte Carlo simulations continue looping for the same set of $M_{i,1}$ until the desired error is achieved, as illustrated in Figures 1 and 2.

III. Once the desired error is achieved, depending on the optimization algorithm strategy, the result of the probabilistic indicator EENS is saved (for comparison purposes with others), and the process is repeated for another set of $M_{i,1}$. Knowing that the process of evaluating in the objecting function each set of $M_{i,1}$ is independent, we use the parallel computing reassure to speed up the solution, as also illustrated in Figures 1 and 2.

IV. This process is performed continuously (1, 2, 3, …, S) determining the estimated decreasing values of the probabilistic indicator $E[Z_1]$, $E[Z_2]$, …, $E[Z_S]$, in this context $EENS_1$, $EENS_2$, …, $EENS_S$.

V. In our case, the optimization process ends (stop criterion) when the difference $E[Z_S] – E[Z_{S-1}]$ is less than 1.0E-06, which is the second conditional statement in the flow diagram of the simulation (see Figure 2).

VI. The set of $M_{i,1}$ (start times for the first maintenance of each generator unit considered in the system) with the lowest probabilistic indicator ($E[Z_S]$) is the solution. In this context, the maintenance scheduling with the lowest Expected-Energy-Not-Supplied (EENS).

VII. End of the optimization algorithm.

In this contribution, we use different optimization algorithms, specifically four options, as it is uncertain which heuristic algorithm is the best for this specific problem.

3. Result and Discussion

This section outlines all the parameters required to execute a scenario. Following this, the scenario is assessed and discussed using the proposed solution. The interim results are then benchmarked against the reference data to validate the initial scenario under equivalent conditions. Finally, modifications are made to the initial scenarios to incorporate elements such as dispersion in maintenance activities in a precise manner, and then, in addition to, wind energy integration using offshore wind farms, which enforces the coordination of a large volume of maintenance activities—two typical conditions in a real Power System with the presence of offshore wind farms.

Parameterization

To validate the proposed solution, the initial scenario used the IEEE Reliability Test System (IEEE-RTS) suggested by the Subcommittee on Applications of Probabilistic Methods. This system was designed to offer a uniform testing environment and is particularly suitable for implementing planning maintenance solutions.

First, we summarize general settings, and then we list the information from the reference paper [9]. Table 2 shows the parameters necessary to model the capacity of the X generator unit system. In this scenario, the system has 32 generators, where individual unit capacities vary from 12 to 400 MW, and the maintenance durations range from two to six weeks. The total generating capacity of the system is 3405 MW.

- β = 5% (error criterion).
- T = 8760 hours (simulation time window)
- N_{MTi} (number of maintenances in the i-th generator unit); $\overline{C}_i$ (nominal generator unit capacity); $MTTF_i$ (Mean-Time-To-Failure in the i-th generator unit); $MTTR_i$ (Mean-Time-To-Repair in the i-th generator unit); $M_{i,k}$ (k-th Time-To-Maintenance of the i-th generator unit); and $D_{i,k}$ (k-th Time-Duration-Maintenance of the i-th generator unit) are shown in Table 2.

Table 2. Parameterization of the scenario.

Number of Units	Unit Capacity (MW) $\overline{C}_i$	Unit Type	$MTTF$ (hours)	$MTTR$ (hours)	$M_{i,k}$ (hours/year)	Scheduled Maintenance (hours/year) $D_{i,k}$	N_{MTi}
5	12	Oil/Stream	2940	60	0	336	1
4	20	Oil/CT	450	50	0	336	1
6	50	Hydro	1980	20	0	336	1
4	76	Coal/Stream	1960	40	0	504	1
3	100	Oil/Stream	1200	50	0	504	1
4	155	Coal/Stream	960	40	0	672	1

Number of Units	Unit Capacity (MW) $\overline{C}_i$	Unit Type	*MTTF* (hours)	*MTTR* (hours)	$M_{i,k}$ (hours/year)	Scheduled Maintenance (hours/year) $D_{i,k}$	N_{MTi}
3	197	Oil/Stream	950	50	0	672	1
1	350	Coal/Stream	1150	100	0	840	1
2	400	Nuclear	1100	150	0	1008	1

Second, the peak demand reaches 2850 MW. Using the cited paper [9], it is feasible to construct hourly load profiles in proportion to peak demand. Figure 3 shows the System Load shape denoted as *Y*.

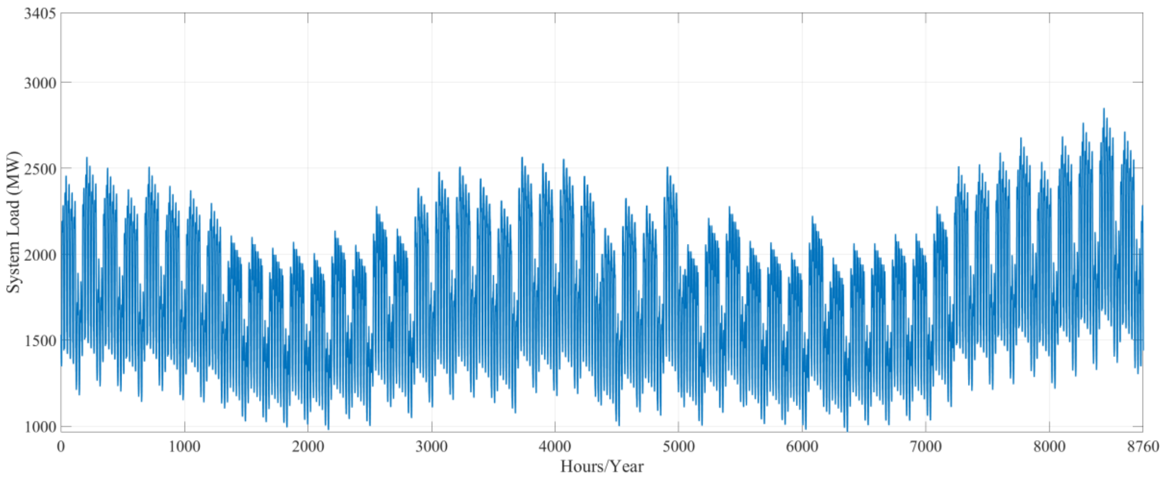

Figure 3. System Load.

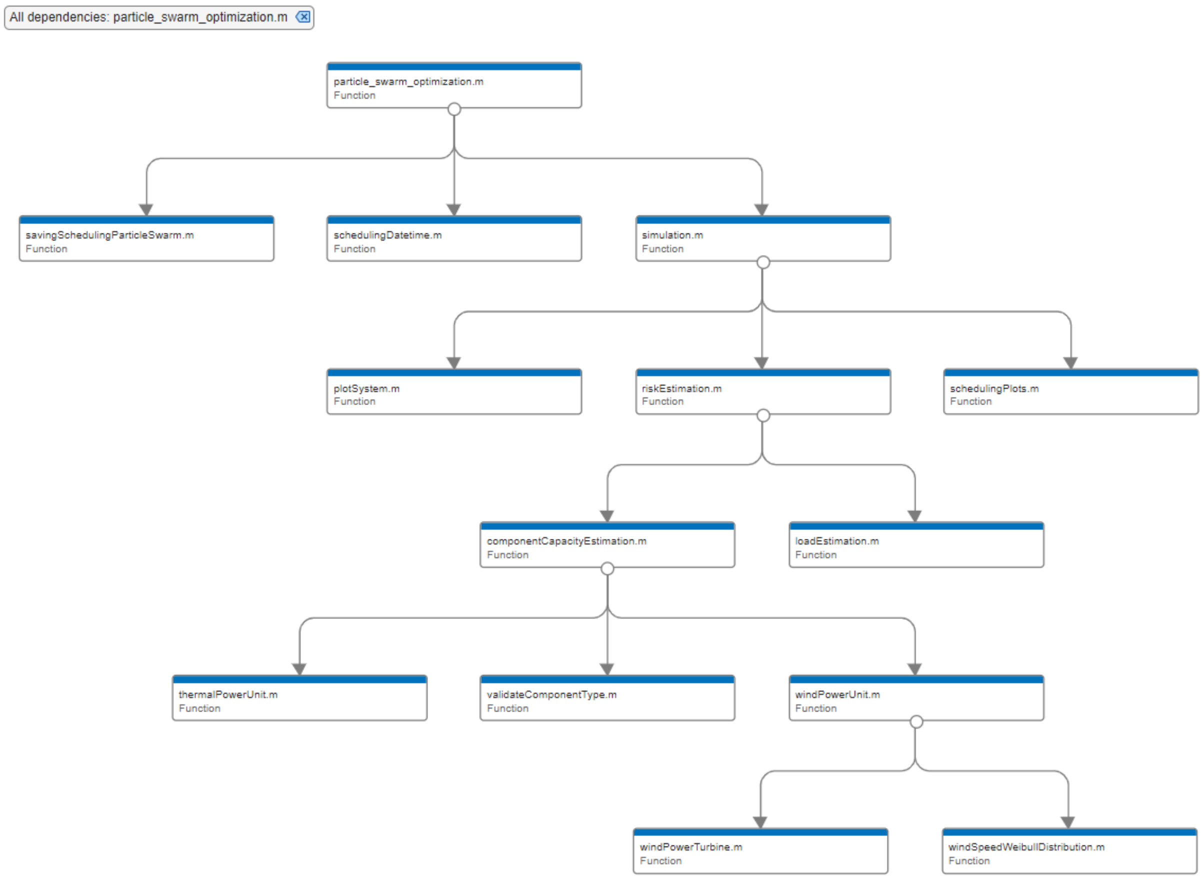

Figure 4. Optimization problem functional dependency analysis, specifically Particle Swarm Optimization (PSO).

Implementation

Implementing the proposed model in a programming language is relevant for several reasons, particularly regarding simulation tasks. We decided to implement the model in MATLAB since the tool is designed to handle computation-intensive tasks, and it is well-accepted in the academy. The code implemented is saved in [22], a public GitHub repository.

As we pointed out above, the implemented optimization routine is a heuristic method. However, thanks to parallel computing, the candidate scenarios are evaluated independently, and the time to reach the final solution is also relatively fast for this type of algorithm, knowing that it depends on the computer power. Figure 4 shows the dependency analysis of the optimization problem and, in some sense, indicates the connection between functions. The solution to the optimization problem is addressed with four heuristic algorithms, specifically, Particle Swarm Optimization (PSO), Nonuniform Pattern Search (NUPS), Surrogate Optimization, and Genetic Algorithm (GA). Figure 4 shows the dependency diagram for the PSO algorithm. Changing the algorithm only impacts the umbrella function; the rest remain the same.

As we can observe in Figure 4, the optimization algorithm function has three dependencies. Two dependencies are related to saving the results, and the other is the simulation function. In the case of the simulation function, two dependencies were implemented to visualize the performance of the scenario, a user interface summarizing key information, and the third dependency is the risk estimation function in charge of estimating the convolution between the stochastic system capacity and the system load, specifically a distribution function describing the energy-not-supplied (ENS) in the scenario evaluated. Then the expected value of the distribution function is the EENS risk indicator. The stochastic system capacity is composed of the contribution of each component capacity, generator units in this case. While the thermal units (Oil/Stream, Oil/CT, Coal/Stream, Nuclear) and Hydro units are considered with primary source of energy always available, wind energy depends on the wind speed and the characteristic function of the wind turbine. Therefore, the function of the wind power unit has two dependencies, the wind speed model and the characteristic function of the wind turbine.

Resolution and Validation

Given the parameterization and knowing the structure of the implementation, we aim to solve and validate the results obtained by the proposed model. First, we compare the probabilistic indicator $E[Z]$, in this context EENS, with another reference, when no maintenance activities are performed. This scenario is equivalent to ignoring maintenance activities in the coming year. Table 3 shows the comparison.

Table 3. Scenario assessment when no maintenance activities are performed.

Source	Risk Indicator EENS (MWh/year)	Simulation Time (seconds)
[2]	1,186	N/A
Proposed	1,184 (β = 5%) [1,125 1,243]	52
Proposed	1,181 (β = 1%) [1,170 1,193]	1,295

As we can see in Table 3, the results are comparable, even assuming a smaller tolerance error, specifically 1%. This result also shows a theoretical reference for the optimization solution. The closer the EENS value, when considering the scheduling of maintenance activities of the generating units, is to the theoretical reference, the better the proposed scheduling will be, since the probability of not satisfying the System Load Y is lower.

As we stated, the accuracy of the Monte Carlo method depends on the standard deviation of the estimated ENS values, and the square root number of simulations N performed. The method implemented thus far does not consider variance reduction techniques, so the number of simulations is the only parameter driving the convergence of the simulation to the desired error. Certainly, increasing the number of simulations decreases the error but also increases the execution time. Table 3 presents the simulation time for the same scenario and for two tolerance errors. As we can see, while the estimated EENS value does not deviate much, the simulation time is significantly longer. All simulations performed for this contribution were executed on a CPU 12th Gen Intel (R) Core (TM) i5-1240P, and given the results in Table 3, we decided to use a 5% tolerance error as a good balance between simulation accuracy and execution time for all the scenarios evaluated in this contribution.

Once the theoretical reference has been validated, references [3], [18], and [21] are selected to compare the proposed optimization solutions. All selected references obtain probabilistic-oriented solutions for the IEEE-RTS system. On the other hand, in our case, we tested a set of four heuristic algorithms. Each of them has different strategies. We used MATrix LABoratory (MATLAB) [23] for the proposed model implementation. Therefore, we use well-implemented algorithms from MathWorks for the model solution. Specifically, Particle Swarm Optimization (PSO), Nonuniform Pattern Search (NUPS), Surrogate Optimization, and Genetic Algorithm (GA) were the cases tested. Regardless of the algorithm strategy, we assume that the optimization process ends when the difference between two consecutive evaluations in the objective function is less than 1.0E-06.

Table 4 shows the set of $M_{i,1}$ provided by each optimization algorithm tested and all references used for benchmarking. Table 5 shows the results of evaluating each set of $M_{i,1}$ (starting time-of-maintenance) in the objective function proposed in this paper. As we can see, the best scheduling of maintenance activities is the solution with the lowest EENS. Also, Table 5 shows comparable solutions (Ref. [3] versus Surrogate, Ref. [18] versus NUPS and GA, and Ref. [21] versus PSO), assuming a 5% error for each. However, given the nature of the problem, even with similar solutions, which means comparable EENS (probabilistic indicator), the scheduling of maintenance activities is completely different. This phenomenon is illustrated in Figures 5, 6, 7, and 8. Regardless of achieving comparable solutions, in this paper, we rely on the EENS indicator to compare and determine the best solution.

At this point, we can partially conclude that the proposed model has been validated. Knowing this partial conclusion, we decided to use all proposed algorithms to evaluate the modifications introduced in the scenario, to consider first dispersion in maintenance activities, and then the integration of wind farms, which imposes the coordination of a large volume of maintenance activities.

Table 4. Maintenance scheduling solutions for IEEE-RTS.

Unit No.	Unit Capacity (MW)	Start Maintenance (hours)						
		Ref. [3]	Ref. [18]	Ref. [21]	PSO	NUPS	Surrogate	GA
1	12	5,544	5,880	2,527	1,298	242	6,150	1,291
2	12	5,208	4,032	7,257	2,295	484	1,175	1,906
3	12	2,184	3,528	7,885	6,936	85	8,384	5,074
4	12	1,008	7,224	3,317	2,723	952	6,424	4,556
5	12	1,008	5,208	327	6,243	890	8,377	6,395
6	20	5,544	3,528	1,809	6,885	940	19	6,147
7	20	5,208	2,856	4,331	2,295	4,374	4,293	2,076
8	20	2,856	7,224	7,248	4,341	2,960	8,251	2,018
9	20	2,184	7,224	1,872	4,962	2,178	7,388	4,817
10	50	6,384	5,040	4,190	5,047	372	7,818	2,423
11	50	4,536	3,192	405	6,567	2,662	3,234	3,396
12	50	3,528	5,208	5,072	6,716	2,904	7	6,186
13	50	2,184	3,528	4,318	5,679	5,194	6,971	6,108
14	50	1,344	5,880	4,222	2,423	1,340	3,611	4,476
15	50	504	3,528	1,849	6,853	6,702	1,140	4,362
16	76	3,360	504	5,043	3,195	1,824	7,839	4,925
17	76	6,048	1,176	5,540	5,857	18	6,205	1,983
18	76	5,712	5,712	5,002	5,750	4,356	4,291	4,031
19	76	2,688	1,848	7	4,281	406	7,448	1,414
20	100	1,176	4,536	6,719	5,469	4,840	3,311	1,759
21	100	5,040	5,880	5,523	1,644	986	4,372	4,423
22	100	4,536	5,208	5,041	2,335	3,276	2,241	5,638
23	155	6,720	2,520	6,376	5,875	1,470	5,644	106
24	155	6,048	4,368	3,006	829	2,224	6,735	6,744
25	155	4,368	1,008	5,959	5,367	1,506	4,399	5,426
26	155	1,680	6,720	4,434	1	2,196	2,265	2,746
27	197	6,552	2,352	1,828	4,206	6,534	1,442	6,082
28	197	2,352	1,680	1,305	5,004	6,584	6,203	1,033

Unit No.	Unit Capacity (MW)	Start Maintenance (hours)						
		Ref. [3]	Ref. [18]	Ref. [21]	PSO	NUPS	Surrogate	GA
29	197	1,512	5,208	6,514	2,292	1,162	1,563	1,149
30	350	5,208	6,384	970	6,223	5,212	6,273	6,290
31	400	1,680	5,712	5,512	1,497	5,710	4,995	5,033
32	400	5,880	1,512	2,015	1,227	5,504	1,309	1,766

Table 5. Probabilistic impact assessment of maintenance scheduling solutions for IEEE-RTS.

Risk Indicator EENS (MWh/year)						
Ref. [3]	Ref. [18]	Ref. [21]	PSO	NUPS	Surrogate	GA
2,768 [2,629; 2,906]	2,492 [2,368; 2,617]	2,143 [2,036; 2,250]	2,089 [1,984; 2,193]	2,425 [2,304; 2,546]	2,840 [2,698; 2,981]	2,316 [2,200; 2,432]

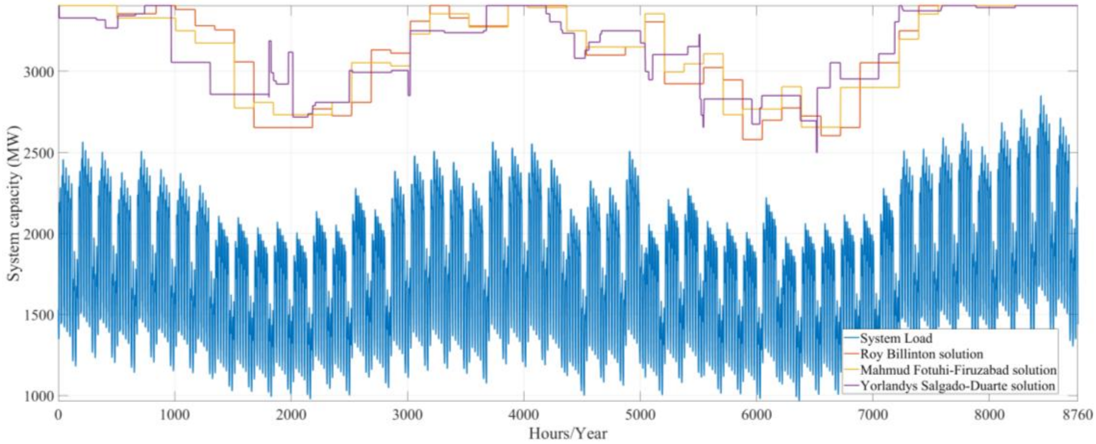

Figure 5. Capacity of the generation system for solutions [3], [18], and [21] versus system load.

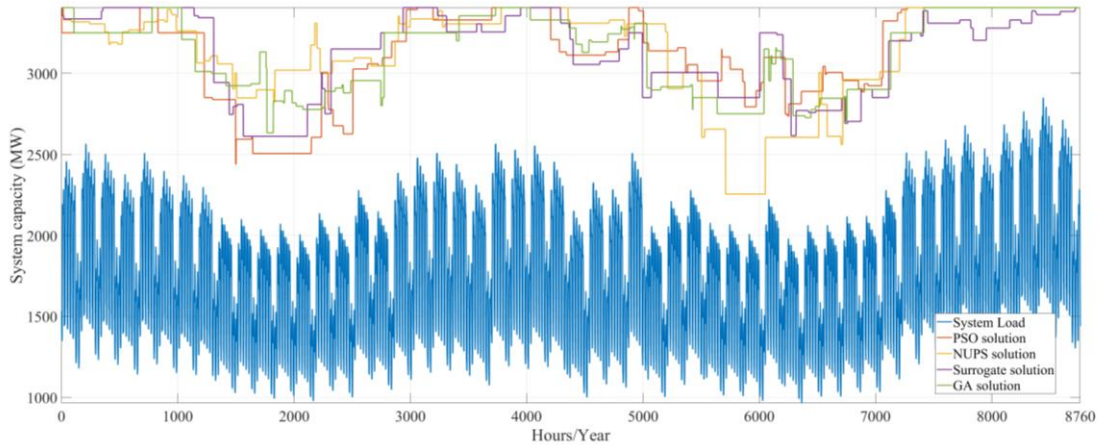

Figure 6. Capacity of the generation system for PSO, NUPS, Surrogate, and GA solutions versus system load.

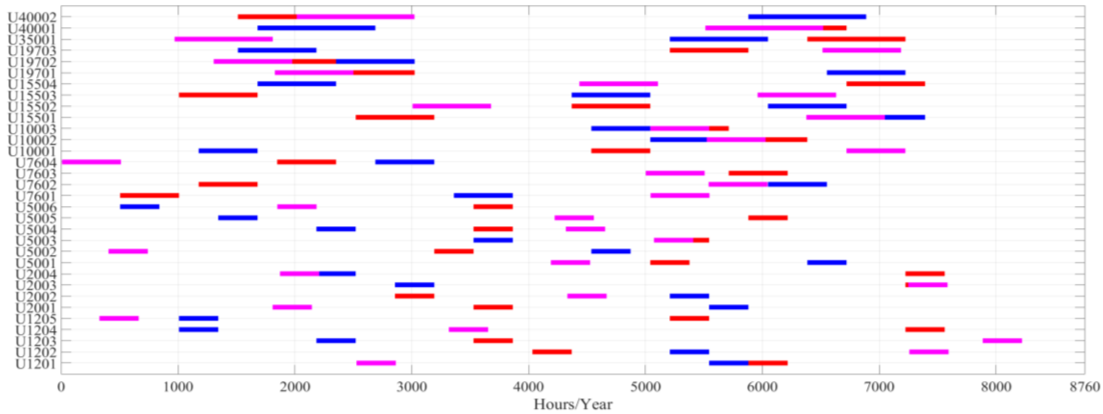

Figure 7. Maintenance scheduling schema for [3], [18], and [21] solutions.

Note that: blue (Roy Billinton), red (Mahmud Fotuhi-Firuzabad), and magenta (Yorlandys Salgado Duarte).

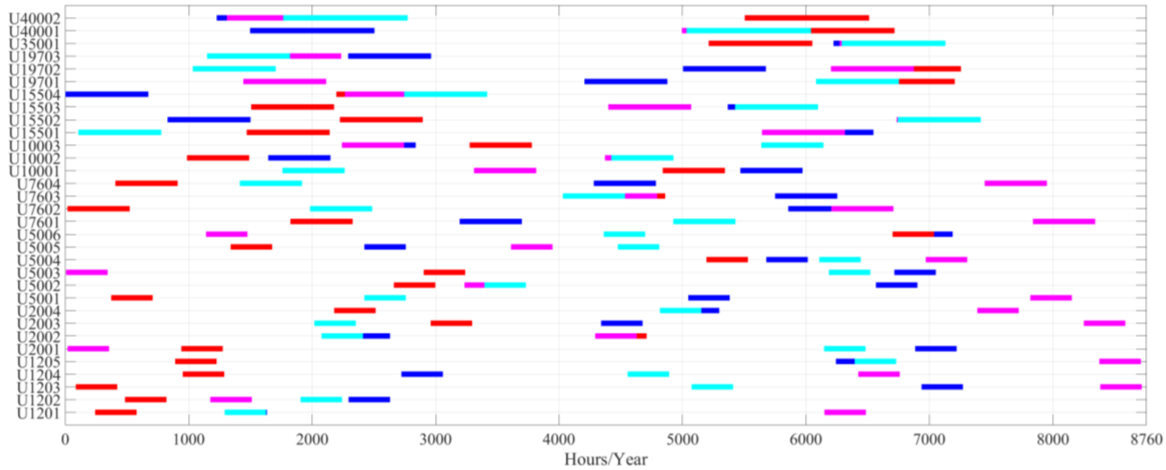

Figure 8. Maintenance scheduling schema for PSO, NUPS, Surrogate, and GA solutions.

Note that the following colors are blue (PSO), red (NUPS), magenta (Surrogate), and cyan (GA).

Dispersion in maintenance activities

The first modification introduced in the scenario is the dispersion of maintenance activities. Table 6 shows the columns with the modifications. The rest remain unchanged (see Table 2 for details). As we can see, the duration of each maintenance $D_{i,k}$ is one week, and there is always one month between them, which means, the Time-To-Maintenance $M_{i,k}$ is one month. Note that the optimization algorithm always provides the first maintenance $M_{i,1}$ in the chain. For this example, we use the same values for $D_{i,k}$, and $M_{i,k}$ in all instances for simplicity; however, the parameters $D_{i,k}$, and $M_{i,k}$ can adopt any value and certainly will depend on the needs of the Power System. At this point, even proposing simplicities, the scenario is closer to reality. Usually, in a maintenance lifecycle, there are operating time constraints between consecutive maintenance activities, and we represent this singularity with $M_{i,k}$. In a generator unit, a maintenance activity $D_{i,2}$ is performed after a certain operation time $M_{i,2}$. As we can see, the proposed solution can allocate maintenance activities in a precise manner.

Table 6. Parameterization of the scenario with dispersed and distributed maintenance activities.

Number of Units	Unit Capacity (MW) $\overline{C}_i$	$M_{i,k}$ (hours/year)	Scheduled Maintenance (hours/year) $D_{i,k}$	N_{MTi}
5	12	672	[168, 168]	2
4	20	672	[168, 168]	2
6	50	672	[168, 168]	2
4	76	[672, 672]	[168, 168, 168]	3
3	100	[672, 672]	[168, 168, 168]	3
4	155	[672, 672, 672]	[168, 168, 168, 168]	4
3	197	[672, 672, 672]	[168, 168, 168, 168]	4
1	350	[672, 672, 672, 672]	[168, 168, 168, 168, 168]	5
2	400	[672, 672, 672, 672, 672]	[168, 168, 168, 168, 168, 168]	6

As we know, the theoretical reference remains unchanged in this modified scenario because the generator unit composition of the system and the volume of maintenance activities (hours of maintenance in one year) are the same. On the other hand, since we changed the scenario, there is no external reference to compare. In this case, we rely on using the four proposed and validated algorithms on the same basis and comparing them, specifically, PSO, NUPS, Surrogate Optimization, and GA.

Table 7 shows the set of $M_{i,1}$ provided by each optimization algorithm for this modified scenario. Table 8 shows the results of evaluating each set of $M_{i,1}$ (starting time-of-maintenance) in the objective function proposed in this paper. Again, the best scheduling of maintenance activities is the solution with the lowest EENS. In this case, the PSO achieved the best solution. This time, not all solutions are comparable assuming a 5% error for each, only PSO and GA. However, we must say that, in this exercise, the computational effort of GA is higher than that of PSO. In other words, from the computational effort point of view, PSO is less demanding because fewer evaluations in the objective function were needed to achieve the solution. Taking the best solution, Figures 9 and 10 illustrate the outcome of the modified scenario.

Even knowing that the volume of maintenance activities is the same in this modified scenario, that is, the number of hours of maintenance in one year, the dispersion introduced is restricting the solution area. It makes sense that the probabilistic indicator EENS achieved in this modified scenario, specifically EENS = 3,311 MWh/year, is higher than the conditions without constraints (base scenario, EENS = 2,089 MWh/year), even when the optimization algorithm is the same. Figures 9 and 10 also visualize this perspective. In the base scenario (no dispersion), the proposed solution better follows the shape of the System Load when aiming to accommodate the maintenance activities over the year.

Table 7. Maintenance scheduling solutions considering dispersed maintenance activities for the IEEE-RTS.

Unit No.	Unit Capacity (MW)	Start Maintenance (hours)			
		PSO	NUPS	Surrogate	GA
1	12	4,704	137	1,527	3,866
2	12	6,057	274	1,814	411
3	12	1,403	6,747	4,879	854
4	12	4,418	4,644	4,305	335
5	12	2,304	685	3,240	1,404
6	20	2,347	4,918	6,440	6,865
7	20	7,394	5,023	1,561	6,206
8	20	7,702	1,096	5,790	439
9	20	4,693	1,233	6,748	688
10	50	5,093	1,274	6,516	384
11	50	6,004	1,507	5,486	1,580
12	50	4,683	1,132	6,974	5,792
13	50	7,167	5,669	6,870	6,535
14	50	1,807	1,870	4,588	717
15	50	5,776	1,525	1,458	5,696
16	76	113	5,008	309	5,106
17	76	5,901	281	5,884	5,558
18	76	5,524	1,442	143	4,205
19	76	5,041	687	1,200	5,019
20	100	676	1,209	6,839	4,979
21	100	0	5,757	522	4,607
22	100	470	5,062	5,822	2,537
23	155	0	4,147	5,303	5,033
24	155	3,842	5,404	4,987	4,356
25	155	2,682	5,569	5,557	538
26	155	5,344	490	2,470	804
27	197	4,854	3,699	487	3,832
28	197	4,525	3,868	2,648	5,382
29	197	508	3,973	3,522	187
30	350	312	14	863	1,144
31	400	963	151	356	2,384
32	400	1,627	4,392	1,476	1,830

Table 8. Probabilistic impact assessment of dispersed maintenance scheduling solutions.

Risk Indicator EENS (MWh/year)			
PSO	NUPS	Surrogate	GA
3,311; [3,145; 3,476]	3,977; [3,779; 4,176]	4,753; [4,516; 4,990]	3,407; [3,237; 3,576]

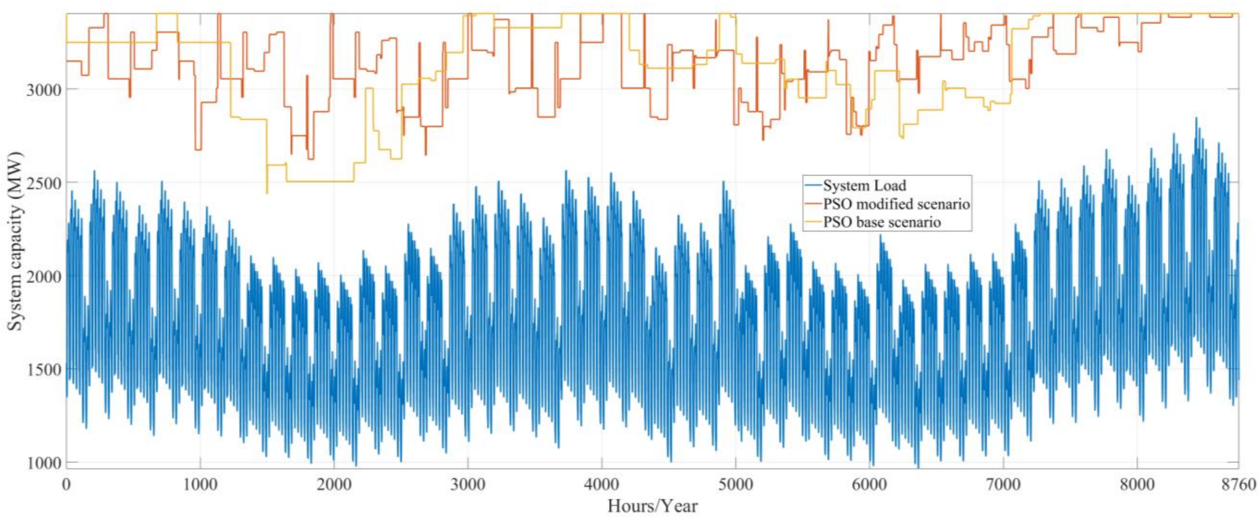

Figure 9. Generation system capacity (base and modified scenario) for PSO solutions versus system load.

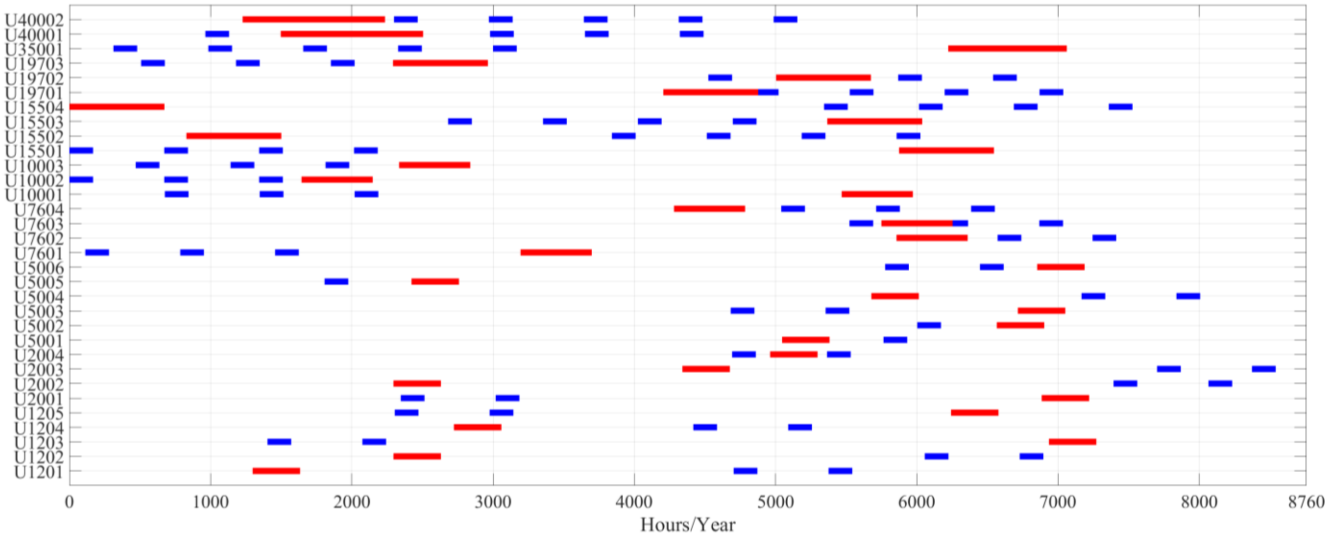

Figure 10. Maintenance scheduling schema (base and modified scenario) for PSO solutions.

Note that blue (PSO scenario modified), and red (PSO base scenario).

Dispersion in Maintenance Activities with Integrated Offshore Wind Farms

The second modification introduced in the scenario, in addition to the previous, is the integration of offshore wind farms. The wind turbine parameters assumed to make up the offshore wind farms modeled in this contribution are listed in Table 9. This new scenario replaced three Oil/Stream generator units of 100 MW by offshore wind farms. Specifically, three farms with 50 wind turbines of 2 MW, adding 300 MW, which is the same capacity as the replaced generator units. Table 10 underlines the parameterization of the new scenario. Also, the wind turbine *MTTF* and *MTTR* values are assumed to be 3650 and 55 hours, respectively. As before, note that the optimization algorithm always provides the first maintenance $M_{i,1}$ in the chain.

In this new scenario, as we introduced three offshore wind farms, the number of individual generator units increased from 32 to 179. This singularity consequently increases the number of maintenance activities to be coordinated exponentially.

Also, since we modified the generator unit composition of the system for this scenario, we reassessed the theoretical reference. Table 11 shows the results. As mentioned previously, the closer the probabilistic indicator EENS value, when considering the scheduling of maintenance activities of the generating units, to the theoretical reference, the better the proposed scheduling will be.

Table 9. Wind speed and wind turbine parameters.

Parameter	Value considered
μ_{sw}	19.52 km/h
σ_{sw}	10.99 km/h
P_r	2 MW
v_{ci}	15 km/h
v_r	36 km/h
v_{co}	80 km/h

Table 10. Scenario parameters after dispersion and integration of the wind farm.

Number of Units	Unit Capacity (MW) $\overline{C}_i$	*MTTF* (hours)	*MTTR* (hours)	$M_{i,k}$ (hours/year)	Scheduled Maintenance (hours/year) $D_{i,k}$	N_{MTi}
5	12	2940	60	672	[168, 168]	2
4	20	450	50	672	[168, 168]	2
6	50	1980	20	672	[168, 168]	2
4	76	1960	40	[672, 672]	[168, 168, 168]	3
4	155	960	40	[672, 672, 672]	[168, 168, 168, 168]	4
3	197	950	50	[672, 672, 672]	[168, 168, 168, 168]	4
1	350	1150	100	[672, 672, 672, 672]	[168, 168, 168, 168, 168]	5
2	400	1100	150	[672, 672, 672, 672, 672]	[168, 168, 168, 168, 168, 168]	6
150	2	3650	55	[672, 672, 672, 672, 672]	[168, 168, 168, 168, 168, 168]	6

Table 11. Scenario assessment with dispersion and integration of the wind farm when no maintenance activities are performed.

Risk Indicator EENS (MWh/year)
5,921 (β = 5%) [5,625; 6,217]

As we have noticed in previous scenarios, the PSO seems to be the best algorithm for this specific optimization problem. Therefore, for this second scenario, we present all the details of convergence of the PSO algorithm. Table 12 shows the set of $M_{i,1}$ provided by the PSO optimization algorithm. Table 13 shows the results of evaluating the set of $M_{i,1}$ (starting time-of-maintenance) in the objective function proposed in this paper. Figure 11 shows the usual convergency plot of the optimization algorithm, Figure 12 shows the capacity of the generator unit system considering only the maintenance activities schema, and Figure 13 shows the scheduling of maintenance activities, which certainly visualizes the complexity of coordination and visualization of a large volume of dispersed activities.

Table 12. Maintenance scheduling solutions for wind farms and dispersed maintenance activities.

Unit No.	Capacity	PSO	
		Start Maintenance	
1	12	1126	'16-Feb 22:00:00'
2	12	1514	'05-Mar 02:00:00'
3	12	7752	'20-Nov 00:00:00'
4	12	5627	'23-Aug 11:00:00'
5	12	4456	'05-Jul 16:00:00'
6	20	4805	'20-Jul 05:00:00'
7	20	1431	'01-Mar 15:00:00'
8	20	7346	'03-Nov 02:00:00'
9	20	4961	'26-Jul 17:00:00'
10	50	6489	'28-Sep 09:00:00'
11	50	5656	'24-Aug 16:00:00'
12	50	5717	'27-Aug 05:00:00'
13	50	30	'02-Jan 06:00:00'
14	50	449	'19-Jan 17:00:00'
15	50	3799	'08-Jun 07:00:00'
16	76	0	'01-Jan 00:00:00'
17	76	3862	'10-Jun 22:00:00'
18	76	5813	'31-Aug 05:00:00'
19	76	3784	'07-Jun 16:00:00'
20	155	5536	'19-Aug 16:00:00'
21	155	273	'12-Jan 09:00:00'
22	155	4565	'10-Jul 05:00:00'
23	155	5355	'12-Aug 03:00:00'
24	197	2649	'21-Apr 09:00:00'
25	197	6071	'10-Sep 23:00:00'
26	197	331	'14-Jan 19:00:00'
27	350	592	'25-Jan 16:00:00'
28	400	1640	'10-Mar 08:00:00'
29	400	1001	'11-Feb 17:00:00'
30	2	3982	'15-Jun 22:00:00'
31	2	401	'17-Jan 17:00:00'
32	2	3792	'08-Jun 00:00:00'
33	2	2129	'30-Mar 17:00:00'
34	2	923	'08-Feb 11:00:00'
35	2	1935	'22-Mar 15:00:00'
36	2	4128	'22-Jun 00:00:00'
37	2	4180	'24-Jun 04:00:00'
38	2	4333	'30-Jun 13:00:00'
39	2	4392	'03-Jul 00:00:00'
40	2	931	'08-Feb 19:00:00'
41	2	1521	'05-Mar 09:00:00'
42	2	1125	'16-Feb 21:00:00'
43	2	1771	'15Mar19:00:00'
44	2	564	'24-Jan 12:00:00'
45	2	3126	'11-May 06:00:00'
46	2	4016	'17-Jun 08:00:00'
47	2	9	'01-Jan 09:00:00'
48	2	4388	'02-Jul 20:00:00'
49	2	1008	'12-Feb 00:00:00'
50	2	3399	'22-May 15:00:00'
51	2	2465	'13-Apr 17:00:00'
52	2	837	'04-Feb 21:00:00'
53	2	4357	'01-Jul 13:00:00'
54	2	921	'08-Feb 09:00:00'
55	2	3823	'09-Jun 07:00:00'
56	2	1641	'10-Mar 09:00:00'
57	2	4392	'03-Jul 00:00:00'
58	2	1208	'20-Feb 08:00:00'
59	2	4192	'24-Jun 16:00:00'
60	2	1054	'13-Feb 22:00:00'
61	2	3883	'11-Jun 19:00:00'
62	2	696	'30-Jan 00:00:00'
63	2	2335	'08-Apr 07:00:00'
64	2	3401	'22-May 17:00:00'
65	2	1117	'16-Feb 13:00:00'
66	2	108	'05-Jan 12:00:00'
67	2	2814	'28-Apr 06:00:00'
68	2	2519	'15-Apr 23:00:00'
69	2	1973	'24-Mar 05:00:00'
70	2	4321	'30-Jun 01:00:00'
71	2	392	'17-Jan 08:00:00'
72	2	2023	'26-Mar 07:00:00'
73	2	2087	'28-Mar 23:00:00'
74	2	1985	'24-Mar 17:00:00'
75	2	318	'14-Jan 06:00:00'
76	2	3988	'16-Jun 04:00:00'
77	2	1506	'04-Mar 18:00:00'
78	2	2181	'01-Apr 21:00:00'
79	2	1625	'09-Mar 17:00:00'
80	2	308	'13-Jan 20:00:00'
81	2	4119	'21-Jun 15:00:00'

82	2	203	'09-Jan 11:00:00'
83	2	828	'04-Feb 12:00:00'
84	2	3105	'10-May 09:00:00'
85	2	2410	'11-Apr 10:00:00'
86	2	55	'03-Jan 07:00:00'
87	2	4236	'26-Jun 12:00:00'
88	2	14	'01-Jan 14:00:00'
89	2	2437	'12-Apr 13:00:00'
90	2	3248	'16-May 08:00:00'
91	2	3140	'11-May 20:00:00'
92	2	437	'19-Jan 05:00:00'
93	2	1148	'17-Feb 20:00:00'
94	2	3469	'25-May 13:00:00'
95	2	4196	'24-Jun 20:00:00'
96	2	4119	'21-Jun 15:00:00'
97	2	4296	'29-Jun 00:00:00'
98	2	3257	'16-May 17:00:00'
99	2	2403	'11-Apr 03:00:00'
100	2	3659	'02-Jun 11:00:00'
101	2	4389	'02-Jul 21:00:00'
102	2	3631	'01-Jun 07:00:00'
103	2	3906	'12-Jun 18:00:00'
104	2	1944	'23-Mar 00:00:00'
105	2	888	'07-Feb 00:00:00'
106	2	1072	'14-Feb 16:00:00'
107	2	965	'10-Feb 05:00:00'
108	2	1359	'26-Feb 15:00:00'
109	2	3786	'07-Jun 18:00:00'
110	2	415	'18-Jan 07:00:00'
111	2	2134	'30-Mar 22:00:00'
112	2	23	'01-Jan 23:00:00'
113	2	1242	'21-Feb 18:00:00'
114	2	2883	'01-May 03:00:00'
115	2	3841	'10-Jun 01:00:00'
116	2	2001	'25-Mar 09:00:00'
117	2	1014	'12-Feb 06:00:00'
118	2	3801	'08-Jun 09:00:00'
119	2	2001	'25-Mar 09:00:00'
120	2	4377	'02-Jul 09:00:00'
121	2	85	'04-Jan 13:00:00'
122	2	1829	'18-Mar 05:00:00'
123	2	4232	'26-Jun 08:00:00'
124	2	1535	'05-Mar 23:00:00'
125	2	3408	'23-May 00:00:00'
126	2	190	'08-Jan 22:00:00'
127	2	2140	'31-Mar 04:00:00'
128	2	3164	'12-May 20:00:00'
129	2	2167	'01-Apr 07:00:00'
130	2	3879	'11-Jun 15:00:00'
131	2	2335	'08-Apr 07:00:00'
132	2	698	'30-Jan 02:00:00'
133	2	1479	'03-Mar 15:00:00'
134	2	1130	'17-Feb 02:00:00'
135	2	148	'07-Jan 04:00:00'
136	2	4083	'20-Jun 03:00:00'
137	2	79	'04-Jan 07:00:00'
138	2	2405	'11-Apr 05:00:00'
139	2	794	'03-Feb 02:00:00'
140	2	21	'01-Jan 21:00:00'
141	2	1355	'26-Feb 11:00:00'
142	2	3707	'04-Jun 11:00:00'
143	2	3210	'14-May 18:00:00'
144	2	3057	'08-May 09:00:00'
145	2	194	'09-Jan 02:00:00'
146	2	3934	'13-Jun 22:00:00'
147	2	2921	'02-May 17:00:00'
148	2	450	'19-Jan 18:00:00'
149	2	979	'10-Feb 19:00:00'
150	2	4152	'23-Jun 00:00:00'
151	2	2718	'24-Apr 06:00:00'
152	2	741	'31-Jan 21:00:00'
153	2	3202	'14-May 10:00:00'
154	2	38	'02-Jan 14:00:00'
155	2	1316	'24-Feb 20:00:00'
156	2	1433	'01-Mar 17:00:00'
157	2	2742	'25-Apr 06:00:00'
158	2	2139	'31-Mar 03:00:00'
159	2	3723	'05-Jun 03:00:00'
160	2	1459	'02-Mar 19:00:00'
161	2	3102	'10-May 06:00:00'
162	2	6	'01-Jan 06:00:00'
163	2	2704	'23-Apr 16:00:00'
164	2	2	'01-Jan 02:00:00'
165	2	139	'06-Jan 19:00:00'
166	2	2327	'07-Apr 23:00:00'
167	2	2126	'30-Mar 14:00:00'
168	2	2398	'10-Apr 22:00:00'
169	2	3244	'16-May 04:00:00'
170	2	1903	'21-Mar 07:00:00'
171	2	22	'01-Jan 22:00:00'
172	2	2924	'02-May 20:00:00'
173	2	4229	'26-Jun 05:00:00'
174	2	1850	'19-Mar 02:00:00'
175	2	106	'05-Jan 10:00:00'
176	2	2480	'14-Apr 08:00:00'
177	2	3145	'12-May 01:00:00'
178	2	3309	'18-May 21:00:00'
179	2	3171	'13-May 03:00:00'

Table 13. Probabilistic impact assessment of maintenance scheduling solutions considering wind farms.

Risk Indicator EENS (MWh/year)
PSO
16,357 [15,541; 17,173]

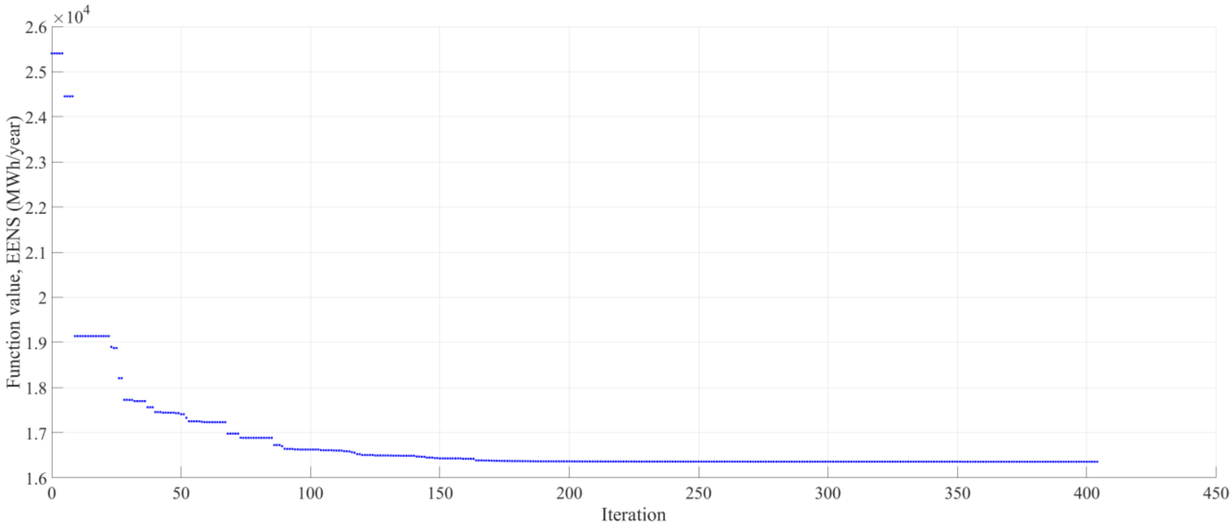

Figure 11. PSO convergence.

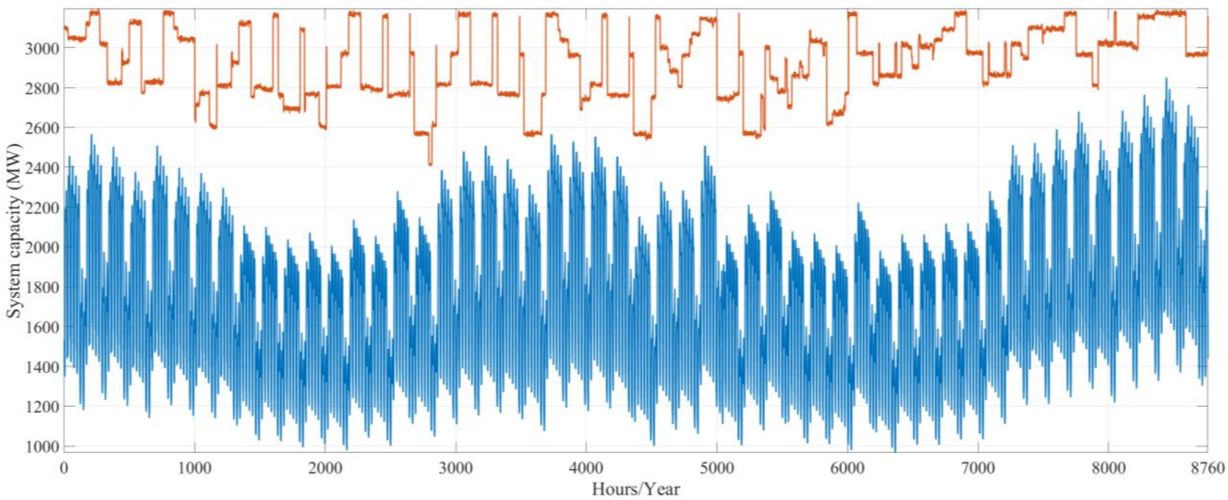

Figure 12. Generation system capacity considering wind farms and only maintenance activities versus system load.

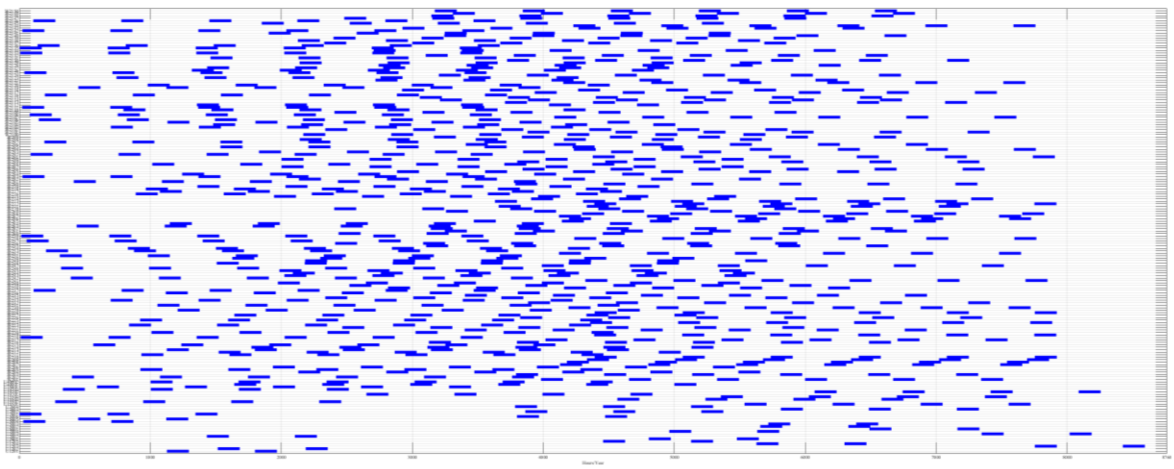

Figure 13. Maintenance scheduling schema considering wind farms.

In all experiments conducted, we have used parallel computing to speed up the estimation of the probabilistic indicator. Since we use heuristic optimization, this feature is fundamental to get results sooner. Certainly, heuristic optimization relies on strategically changing the independent variables ($M_{i,1}$ in our case) and evaluating the objective function (EENS in our case) to know through comparisons where to move next, and of course in the direction of the minimum, either local or global. Knowing that each evaluation is independent, even knowing that each algorithm has different strategies, the sooner we get the evaluations, the faster the comparison will be. Therefore, parallel computing speeds up the optimization process by the number of physical cores involved in independent evaluations. In our case, we use a CPU 12th Gen Intel (R) Core (TM) i5-1240P, which has 12 cores. Independently of the CPU frequency, a parallel process here will be 12 times faster than a series process. In other words, if the elapsed time of a series process is 12 days, a parallel process is 1 day.

4. Conclusions

This study presents a comprehensive probabilistic-oriented twin model to optimize the scheduling of dispersed maintenance activities for offshore wind farms within Power Systems. The model integrates advanced probabilistic approaches, heuristic optimization algorithms, and digital twin frameworks to address the inherent complexities of maintenance scheduling in wind-integrated Power Systems. The proposed model employs a probabilistic approach using Monte Carlo simulations to estimate the Expected-Energy-Not-Supplied (EENS) due to maintenance activities. This approach effectively handles the uncertainties and dynamic nature of integrated wind energy power systems.

The model was validated using the IEEE Reliability Test System (RTS), which demonstrates its precision. Various scenarios, including dispersion in maintenance activities and integration of offshore wind farms, were assessed, showing the model's adaptability to different conditions. The introduction of dispersed maintenance activities and the integration of offshore wind farms increased complexity but provided a more realistic representation of actual maintenance operations.

In this contribution, we assume a homogeneous Weibull distribution throughout the year to simulate the wind. We plan to extend the option of using seasonal parameters for the Weibull distribution, and correlated wind simulations using copulas, since we believe that the energy delivered in two wind turbines closely located would be similar and the wind characteristics can change seasonally. The study tested four heuristic algorithms: PSO, NUPS, Surrogate, and GA. Among these, the PSO algorithm demonstrated the best performance in minimizing EENS, as presented in Tables 4 and 7, highlighting its effectiveness for maintenance scheduling in complex systems. However, when using heuristics, the global minimum is uncertain. Therefore, knowing this limitation, we plan additional sensitivity analyzes to find the best algorithm, certainly, in two directions, testing more heuristics and more scenarios under the same conditions, using a formal experiment design.

The proposed probabilistic-oriented twin model offers a robust solution to optimize maintenance schedules in Power Systems. The integration of probabilistic modeling, simulations, digital twin framework, and heuristic optimization provides a powerful tool to improve the reliability and performance of renewable energy systems. Future work will focus on refining the model parameters, exploring additional optimization algorithms, and extending the model's applicability to other types of renewable energy sources.

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