Cost-Benefit Analysis of Maintenance Plans: Case Study of the Power System of a Large Industrial Facility

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***Abstract*—Maintenance plans aim to reduce the frequency of failures by maintaining components before their state of degradation reaches an undesirable level. These plans must balance the cost of performing maintenance against their benefits, i.e., a reduction in supply interruptions. This paper proposes a stochastic cost-benefit framework to develop maintenance plans that optimally balances these costs and benefits on an array of randomly generated scenarios in a power network. We implement this framework through optimization via simulation. We simulate the effect of various maintenance actions on the availability and degradation state of network components, failures due to human errors, and system operation (including demand curtailments). Based on these results, we assess the costs and benefits of these actions and find the best stream of Maintenance and Inspection (M&I) actions scheduled in time. We apply this approach to the power system supplying a large industrial facility to assess the impact of both offline and online inspections, as well as preventive and corrective maintenance actions. We take advantage of the flexibility of the proposed approach to quantify the potential benefits of online condition monitoring, analyze strategies to hedge against simultaneous outages, and study the relative value of asset redundancy and maintenance plans in enhancing reliability.**

***Index Terms*—Maintenance and inspection, condition monitoring, optimization via simulation, power system reliability.**

I. Introduction

UNPLANNED outages can result in substantial financial losses due to the consequences of supply interruptions and the cost of repairs. The frequency and impact of such outages can be reduced if vulnerable components are maintained or replaced before their failure probabilities exceed acceptable levels, either due to normal aging or exposure to adverse environmental conditions [1]. Maintenance and component replacement in power systems is expensive, not only because of the cost of labor and materials, but also because it decreases redundancy, leaving the system more exposed to unplanned outages. Devising maintenance plans that optimally balance maintenance costs and reliability enhancements is thus of great importance [2].

This paper proposes an integrated reliability-and-economic framework to determine optimal maintenance plans, using a stochastic optimization model based on simulations, applied on a power system supplying a large industrial facility. This model can compute the benefits of M&I actions through detailed simulations of the effects of maintenance on assets and the system. These simulations are complemented with optimization in a two-stage process, allowing us to balance these benefits against their costs. In its first stage, namely the "optimizer", the model develops maintenance and inspection plans that the second stage, namely the "simulator", tests using sequential Monte Carlo simulations. The main sources of uncertainty that are taken into account by these random scenarios are failures, the evolution of equipment degradation processes (making a distinction between the actual degradation and that observed during inspections), and the effects of maintenance. The latter includes not only the improvements in the states of degradation but also human errors during the reconnection of the equipment. These stochastic simulations produce expected values of the costs and reliability metrics for each M&I plan proposed by the optimizer. Based on these results, the optimizer tunes the parameters of the maintenance policy. The simulator and the optimizer iterate until an optimal M&I plan is found. Tuning policy parameters is better aligned with industrial practices than directly scheduling M&I actions. To demonstrate the effectiveness of the proposed approach, we analyze the costs and benefits of conventional and innovative maintenance strategies on the power supply network of an industrial facility. Overall, this paper features the following specific contributions:

1) It proposes an integrated reliability-and-economic framework that can simultaneously schedule various maintenance and inspection actions on large-scale power systems, consisting of different types of assets and

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components, balancing long-term costs and benefits. These actions also include offline and online inspections as well as preventive and condition-based maintenance.

2) It showcases a stochastic optimization-via-simulation approach that implements the above-mentioned framework and applies it on the power system of a large industrial facility. As the model optimizes via simulations, it can capture, within the decision-making process, a more detailed representation of the effects of M&I actions on the health of the equipment (not only in terms of the improvements in the state of degradation but also the possibility of human error). The model can also capture the random evolution of degradation that causes failure events (which may lead, in turn, to supply interruptions), and the difference between the observed evolution of equipment degradation and the actual evolution of degradation.

We use the proposed model to determine the optimal schedule of various M&I actions, quantify the effects of maintenance and inspection plans on continuity of supply, and compare the reliability and economic benefits of M&I actions against those of asset redundancy. We also compare the reliability and economic performance of online monitoring and inspection actions, against that of offline inspections and periodic maintenance actions.

The rest of the paper is organized as follows. Section II reviews the relevant literature. Section III describes the proposed model used to determine optimal maintenance and inspection plans. Section IV presents the case studies, whose results are analyzed in Section V. Section VI concludes.

II. Literature Review

Maintenance plans of power systems have traditionally aimed at scheduling a predefined set of maintenance actions to minimize costs [3]–[5], maximize reliability levels [6], or optimize other metrics of interest to facility owners [7]. These methods are usually limited to arranging a provided set of actions in a schedule without examining the resulting balance between the economic costs of these actions and their reliability benefits. Other types of maintenance plans widely studied in power systems are based on the concepts of reliability-centered maintenance (RCM) [8], [9]. RCM is a qualitative approach to scheduling maintenance actions that prioritizes components that are more critical for system operation [10]. The prioritization of maintenance actions is based on heuristics that usually consider the relation between their costs and their benefits in terms of increased system reliability [11], [12], thereby identifying cost-effective actions.

In order to devise optimal maintenance plans, it is paramount to capture the contribution of maintenance actions in preventing component failures. This requires modeling the underlying degradation processes that trigger unplanned outages, along with the effect of maintenance actions in terms of state-of-health recovery. Furthermore, modeling degradation processes allows us to analyze plans that take advantage of information related to the health condition of assets gathered through inspections. Lately, this approach has received significant attention in power systems [13]–[15]. Endrenyi [16], proposes a simple method to consider the degradation of components in the context of maintenance. Multiple states of degradation leading to failures are represented by state diagrams, and modeled through Markov processes. Inspection actions are modeled using additional states, where information regarding the state of degradation of the asset is revealed. This information is then used to determine whether maintenance actions are needed.

State-diagram models have been used to study the maintenance of single components, analyzing different performance metrics [17], and considering additional details, such as delay times and aging [18]. These models have also been used to determine optimal maintenance and inspection plans for multiple components within a power system [19], [20]. In [19], the inspection rates of different substation components are optimized, aiming at maximizing reliability. Zhong *et al.* [20] determine inspection rates that minimize the total cost of the system. However, these models cannot capture how maintenance actions are actually scheduled in practice. Instead, they assume that inspection times follow a given probability distribution. This prevents the coordination of maintenance actions among different system components, which is of the utmost importance in power systems. Note that the proposed framework to optimize maintenance plans does not present this problem, as it replicates how maintenance actions are scheduled in practice, including the coordination between maintenance of different components.

Determining optimal M&I plans for power systems in a cost-benefit fashion is fundamentally challenging for two main reasons. Firstly, the benefits of maintenance in reducing supply interruptions are difficult to compute. Maintenance prevents failures by improving the degradation state of components. Therefore, to capture its benefits, it is necessary to model its impact on the stochastic degradation processes that drive unplanned outages. Secondly, the decision rationale used to schedule maintenance and inspections should consider system conditions that change over time, such as the availability state of components, the operating conditions, and information gathered through inspections regarding the states of degradation.

The complexity associated with optimizing maintenance plans for modern systems (including power systems) has prompted the need for more flexible tools to address this problem. In this context, simulation-based optimization has emerged as an attractive alternative to optimize maintenance plans, as many maintenance policies cannot be treated analytically, and because simulations provide the flexibility needed to capture the complexities and details of a real-world system [21]. Reference [22] proposes a modeling approach to optimize maintenance plans based on simulations, minimizing the use of the oversimplifying assumptions usually required in optimization models with analytical solutions. In this way, it is able to capture the interactions between maintenance actions and their effects on both components and the operation of the system as a whole. A simulation-based optimization approach is proposed in [23] to determine the optimal maintenance frequency in a manufacturing system, capturing the interactions between maintenance and production.

Maintenance optimization via simulation has also been applied within the context of power systems. Tian *et al.* [24] use this approach to optimize a condition-based maintenance policy for wind power generators that is characterized by two failure probability thresholds. If the first threshold is exceeded, maintenance is performed in the component. Additionally, when maintenance is carried out (due to the first threshold), all other components whose failure probability exceeds the second threshold are also maintained, taking advantage of the fact that a maintenance crew will be sent to the wind farm due to the maintenance triggered by the first threshold. Detailed simulations of the evolution of the system are used to optimize the value of these two thresholds. Santos *et al.* [25] optimize a maintenance policy for offshore wind generators that involves two numerical parameters, one related to the frequency of maintenance actions and another one to their effectiveness. Simulations that consider the logistics associated with maintenance actions determine the optimal value of the policy parameters. The scheduling of preventive maintenance actions for generators is optimized in [26], where the objective is to minimize the loss of load probability of the system. The use of simulations allows quantifying the impacts of different schedules in the operation of the power system. Reference [27] proposes a framework to determine the optimal maintenance strategy of a power system using simulations that model in great detail the logistics associated with spare parts and maintenance works. Heo *et al.* [28] compute the costs and benefits of different maintenance plans using sequential simulations of a power system. They model the degradation of system components, the results of maintenance actions, and the effects of outages on the system.

To the best of the authors' knowledge, the framework proposed in this paper is the first research effort to optimize power system maintenance in an integrated reliability-and-economic fashion, capturing the interaction between the components' degradation states and M&I actions. We do so by using simulations that model the evolution of the degradation state of components and the impact of maintenance and inspection actions in terms of improving and estimating this state, respectively. We also consider that unintended failures can occur due to human errors committed while performing these actions. Through these simulations, we are able to compare maintenance strategies and other asset-heavy alternatives (such as network redundancy) with regards to improving system reliability in a cost-effective fashion.

III. Stochastic Cost-Benefit Modeling Framework for Maintenance Plans

A. Overview

From a cost-benefit perspective, the optimal maintenance plan minimizes the sum of the expected costs of interruptions and the expected costs of performing maintenance actions. Since the common industrial practice is to carry out maintenance according to a policy, we propose to optimize this policy. A maintenance policy consists of a set of rules that prescribe how M&I actions should be scheduled and undertaken. The numerical parameters of such a policy determine the frequency or rate at which inspections and preventive maintenance actions are carried out. They also dictate when to undertake maintenance actions triggered by the inspection results and how to coordinate and prioritize maintenance activities. A M&I plan is an instantiation of a maintenance policy, and the optimal plan is the one that optimally balances the costs of M&I actions and the cost of unsupplied energy. This section describes how the proposed model determines the minimum-cost M&I plan for a particular system by selecting the optimal set of parameters of the maintenance policy. This model consists of two modules, the optimizer and the simulator. As Fig. 1 illustrates, the optimizer selects the parameters of the policy used to schedule M&I actions, while the simulator calculates the effects of the resulting M&I plan using sequential Monte Carlo simulations. These two modules iterate until the optimal M&I plan has been determined. Using the terminology of sequential decision analytics pioneered by Powell [29], the proposed model corresponds to a sequential decision model, as it is composed of a sequence of steps (e.g., days), where decisions are made and new information is revealed. Furthermore, we tune the parameters of a policy consisting of a set of rules used to determine these decisions, hence our solution approach falls into the policy function approximation class.

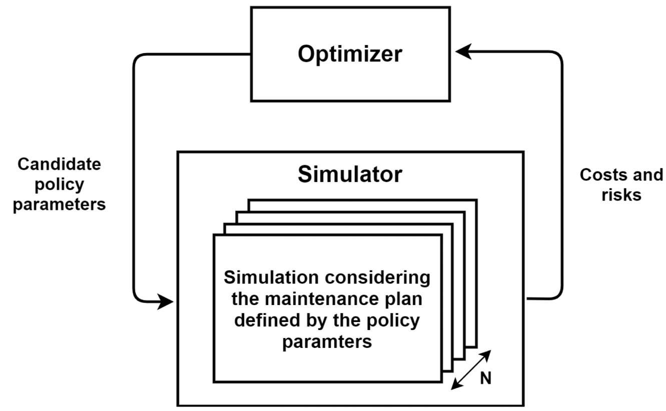

Fig. 1. Schematic representation of the proposed framework.

B. Maintenance Policy

The rules defining a maintenance policy must take into account the current state of the system, which includes the grid topology and its changes due to outages, degradation information gathered through inspections or continuous monitoring, and dates of past M&I actions carried out on each component.

In this paper, we consider a maintenance policy that covers the following four types of M&I actions:

1) Corrective Maintenance (CM) actions carried out to repair components that have failed.
2) Preventive Maintenance (PM) actions performed periodically on components, irrespective of their states of degradation.
3) Periodic inspection actions carried out to collect information regarding components' states of degradation.

4) Inspection-Induced Maintenance (IIM) performed to improve a component's condition if the results of an inspection reveal that its degradation is too high.

The optimizer adjusts the following three parameters of the maintenance policy to find the optimal M&I plan:

1) Frequency of preventive maintenance actions (x_1): This parameter determines the interval of time between two consecutive PM actions. We can study the case where preventive maintenance is not part of the policy by setting this frequency to zero ($x_1 = 0$). In practice, the period between maintenance actions is not constant because some of them are triggered by unplanned outages or prompted by the results of an inspection.
2) Frequency of inspection actions (x_2): This parameter defines the time between the last and the next scheduled inspections. When an asset undergoes unplanned maintenance actions, the time since the last inspection is reset. This frequency or rate can be set at a high value to reflect condition monitoring, where information about the state of components is continuously gathered.
3) Threshold for inspection-induced maintenance (x_3): This parameter defines the minimum degradation level that prompts maintenance actions after an inspection is carried out.

Note that the frequency of PM actions (x_1) must be selected for each PM action considered in the maintenance policy. Similarly, the frequency of inspections actions (x_2) and the threshold for IIM (x_3) must be selected for each inspection action. If these parameters are set for the whole system, they form a set of scalar values. On the other hand, if they are set separately for each type of component, they constitute a set of vectors.

It is important to consider that we have chosen a maintenance policy that schedules inspection and preventive maintenance actions based on elapsed time. An alternative aligned with traditional preventive maintenance concepts would be to schedule these actions based on utilization. In such policies, parameters x_1 and x_2 must be metrics of accumulated loading, such as the amount of energy that has flowed through the component, rather than time.

C. The Simulator: Assessing the Effects of Maintenance Plans

This module calculates the costs associated with a M&I plan defined by a set of policy parameters. In order to do so, it simulates the operation of the power system along with the execution of the M&I actions scheduled by the M&I plan. As it proceeds, it tallies the cost of performing M&I actions and the cost of energy not supplied because of outages. The total cost of operating the system is the sum of these two costs. Because this simulation involves the occurrence of stochastic events, such as component failures, it must be repeated enough times to obtain an estimate of the expected value of the costs and of other probabilistic metrics that can be used to compare the performance of different M&I plans.

The proposed model replicates operational and M&I decisions on the electricity supply system by sequentially simulating its evolution. In order to properly compute the total cost under a given M&I plan, the simulation must extend over a sufficiently large timespan (e.g., several years); otherwise, it won't be able to capture the effects of slow processes such as component degradation. On the other hand, the time resolution of the simulation must be sufficiently fine to model events that span only a few days, such as inspection actions. Therefore, the proposed model simulates several years of operation, with daily resolution for activities and decisions regarding operation and maintenance. Fig. 2 shows the structure of each simulation, where $t_{\max}$ is the number days considered.

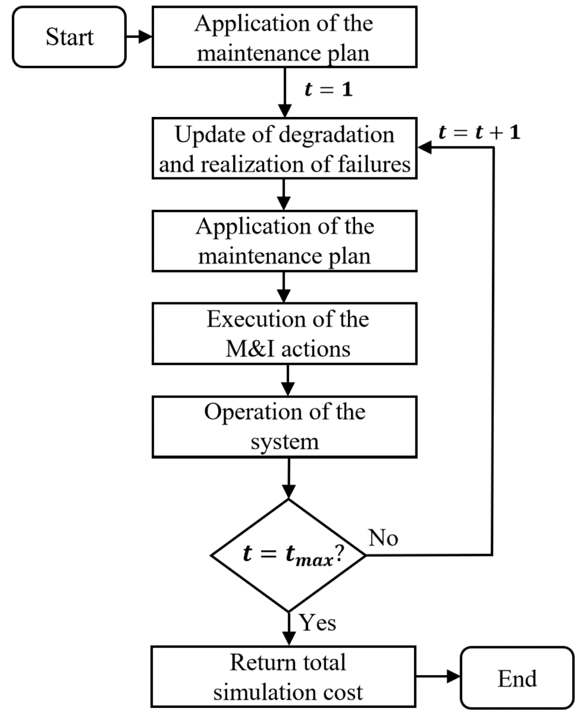

Fig. 2. Flowchart of the simulation module.

At the beginning of each simulation, the M&I plan is applied to determine the first schedule of M&I actions, taking as an input the initial condition of the system, the results of past inspections, and dates of past M&I actions. Then, each day is simulated sequentially in four stages:

1) Update of degradation and realization of failures: Components that have completed their time under offline M&I actions are put back in service, and the state of degradation is updated for all components. Additionally, unplanned outages occurring during this day are determined.
2) Application of the M&I plan: The maintenance schedule is updated according to the M&I policy to account for changes in the state of the system, such as unplanned outages and the results of inspections. For example, the M&I plan may require to postpone some preventive maintenance actions if a critical component has failed.
3) Execution of the M&I actions: Maintenance and inspection actions are performed. If the action must be carried out offline, the component is taken out of service for the necessary number of days.

4) Operation of the system: The system is operated considering the current availability of components, which is defined by the ongoing planned and unplanned outages. The main objective of this step is to compute the loading of each element and the energy not supplied during the day.

Once a scenario has been simulated, its total cost is computed by adding the M&I expenses and the interruption costs for each day. The user sets the number of simulations to be performed with random realizations of the stochastic parameters across the days. The following subsections describe in detail the four stages of the simulation process.

1) Update of Degradation and Realization of Failures: The state of degradation of a component is represented by a degradation percentage that ranges from 0% to 100%. Degradation of 0% represents an *as-good-as-new* state, whereas 100% represents a state of total degradation in which the component cannot operate. Degradation evolves according to a non-decreasing stochastic process $Z_i(t)$ that is updated at the beginning of each day t for every component i. The rate of degradation depends on the component's level of utilization i.e., highly-loaded components degrade faster. At the beginning of the simulation, a degradation speed, v_i, is randomly selected for each component (a number between 0 and 1), representing the probability of degradation increasing after each day. Under nominal loading, degradation increases in steps of 1%, however, we consider steps of magnitude F_{it} in order to account for the components' loading. This value may be greater than 1% if degradation is accelerated (loading higher than nominal) or lower than 1% if it is decelerated (loading lower than nominal). The probability distribution of degradation speeds is calibrated, so each component's failure probability matches historical data of failures at different ages under nominal loading, thus capturing the aging processes of different components. Mathematically, the evolution of the degradation state of components is modeled by Eq. (1), where ω_{it} is a random variable uniformly distributed over the interval $[0, 1]$.

$$Z_i(t+1) = \begin{cases} Z_i(t) + F_{it} & \text{if } \omega_{it} \leq v_i \\ Z_i(t) & \text{otherwise} \end{cases} \tag{1}$$

In practice, the degradation level of a component does not entirely determine the occurrence of unplanned outages. We capture this by linking degradation with failure probabilities through an outage likelihood function. In this way, components may undergo outages at degradation levels lower than 100% with given probabilities. The outage likelihood function quantifies our confidence in degradation being able to characterize components failure. Ideally, if unplanned outages were entirely a consequence of high degradation, then the outage likelihood function would be a step function. In practice, logistic functions can be used to represent outage likelihood, capturing the effect of a variable (degradation) on a binary state (operating or failed). Eq. (2) is an example of such a logistic function, where β_0 and β_1 can be calibrated considering different sources of information, such as failure records, manufacturer data, and expert knowledge.

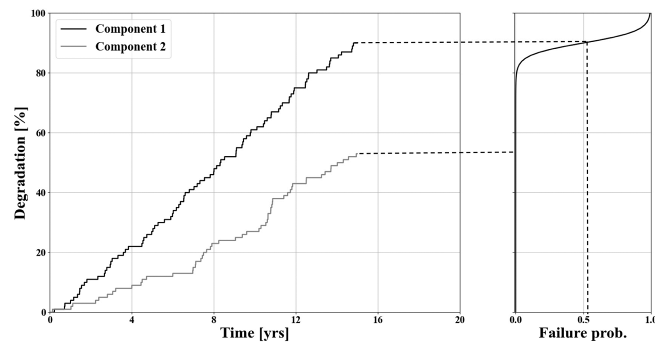

Fig. 3. Components' degradation and its relation with the probability of failure.

$$\mathcal{L}(Z) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 Z)}} \tag{2}$$

Fig. 3 illustrates how two components degrade over 15 years, and how this determines failure probabilities. Component 1 degrades faster than component 2, because its degradation speed parameter is larger ($v_1 > v_2$). After 15 years, the failure probability of component 1 is close to 0.5, whereas the failure probability of component 2 is practically zero. This illustrates that degradation determines the probability of undergoing unplanned outages instead of directly determining their occurrence.

2) Application of the M&I Plan: In this stage, the M&I plan is used to reschedule M&I actions considering newly available information, including the occurrence of unplanned events such as failures, and results from inspections. For example, if a component fails during the previous stage (update of degradation and realization of failures), the maintenance schedule is adjusted to carry out corrective maintenance as soon as possible, potentially postponing other M&I actions. Importantly, this rescheduling process respects the value of the policy parameters already set (e.g., rate of inspections) but accommodates needed M&I actions that have to be carried out immediately due to failures and inspections' results.

3) Execution of M&I Actions: Three types of M&I actions are carried out during this stage.

1) Corrective maintenance to repair components that have failed.
2) Preventive maintenance actions performed on a time-based approach, that is, without considering the state of degradation of components.
3) Inspection-induced maintenance actions carried out when the observed state of degradation is higher than a predefined threshold. In this way, these maintenance actions are triggered by the value assessed during the inspection, not by the actual state of degradation, which is unknown.

When one of these maintenance actions is performed, the component is taken out of service for a predefined number of days during which maintenance is carried out. When this period finishes, the component is connected back in service. The state of degradation after maintenance is not necessarily *as-good-as-new*. Instead, this state is a random variable following a probability distribution that characterizes the effectiveness of the maintenance action undertaken (i.e., more effective maintenance actions attain, in average, lower degradation levels for the component connected back).

The objective of inspection actions is to obtain information about the actual state of degradation of components. The information gathered through these actions is not perfect; therefore, the observed degradation (i.e., the inspection result's numerical value) may differ from the actual degradation value. This is captured by modeling the observed degradation as a random variable with a predefined probability distribution. The characteristics of this distribution depend on the accuracy of the inspection action undertaken. Throughout this work, we consider that the observed degradation follows a normal distribution with an expected value equal to the actual state of degradation and a standard deviation depending on each action's accuracy. Inspections can be offline, if the component needs to be taken out of service, or online if it can be carried out while the component is operating. Similar to maintenance actions, the component is taken out of service for a predefined number of days to perform offline inspections. The result of the inspection is made available when it is connected back in service.

Another relevant feature of the simulation model is that it considers unplanned outages caused by human errors made during maintenance and offline inspections. After these actions are carried out, the likelihood that a component will fail is higher than that determined solely by the new degradation state, due to the probability of human errors. As Eq. (3) shows, this enhanced probability of failure vanishes over a few days i.e., if a component is reconnected on day t^*, the probability of failures due to human errors, $\mathcal{E}$, follows a decreasing function f for T days, after which it becomes zero.

$$\mathcal{E}(t > t^*) = \begin{cases} f(t - t^*) & \text{if } t - t^* \leq T \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

4) Operation of the System: This stage first determines the power flow through each component during the day because this flow affects its rate of degradation. It then computes the amount of energy that cannot be supplied during that day due to planned (e.g., preventive maintenance) and unplanned (e.g., failures) component outages. Flows are computed using active power-only, dc power flow equations because this approach is computationally efficient, which is essential considering the need to simulate thousands of scenarios.

D. The Optimizer: Finding the Best Maintenance Plan

The optimizer determines the optimal parameters of the maintenance policy that, in turn, define the optimal M&I plan. The performance of M&I plans is represented by a general function $\phi(x)$ of unknown structure that we aim to optimize over a search space Θ, consisting of all feasible sets of policy parameters. As shown in Eq. (4), we select the expected cost $\mathbb{E}_\xi[C(x,\xi)]$ as the function $\phi(x)$ to be minimized. This cost includes not only the costs of unsupplied energy but also the direct costs of M&I.

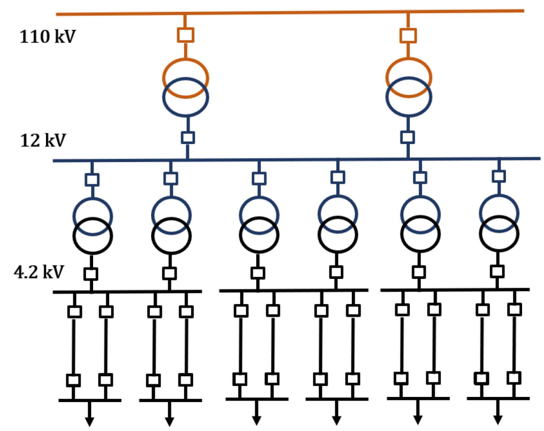

Fig. 4. Power network analyzed.

Since the optimization procedure is general it can be applied to any function $\phi(x)$.

$$\min_{x \in \Theta} \{\phi(x) = \mathbb{E}_\xi[C(x,\xi)]\} \tag{4}$$

The total cost of the M&I plan depends on the vector of parameters x and on the realization of the uncertain scenario ξ (failures of components, evolution of equipment degradation, etc.). This cost can be disaggregated as shown in Eq. (5), where $C(x,\xi)$ is the total cost, $CMI(x,\xi)$ is the cost of planned maintenance and inspections, $CCM(x,\xi)$ is the cost of corrective maintenance, and $CENS(x,\xi)$ is the cost of energy not supplied.

$$C(x,\xi) = CMI(x,\xi) + CCM(x,\xi) + CENS(x,\xi) \tag{5}$$

The simulator computes the total cost of a M&I plan for a specific realization of the uncertainty (i.e., one scenario). A sufficient number of Monte Carlo simulations must be carried out to estimate the expected cost of such a plan. Eq. (6) shows the function $\phi(x)$ that is optimized, where N is the number of times that the simulator is run to approximate the expected cost.

$$\phi(x) = \frac{1}{N}\sum_{i=1}^{N}\big(CMI(x,\bar{\xi}_i) + CCM(x,\bar{\xi}_i) + CENS(x,\bar{\xi}_i)\big) \tag{6}$$

The optimal parameters are determined using a black-box optimization algorithm that only needs to evaluate the objective function and does not require an analytical representation of this function. Specifically, we use a derivative-free optimization approach based on the Radial Basis Function method, available on COIN-OR [30].

IV. Application and Input Data

A. System Description

The system illustrated in Fig. 4 represents the electricity supply network of an industrial facility, and provides the basis for the case studies presented in this section. The system is designed according to the spot network approach [31], where the secondaries of each pair of transformers are connected, and where there is physical redundancy for every component.

TABLE I
ANNUAL FAILURE PROBABILITY OF COMPONENTS OF DIFFERENT AGES UNDER NOMINAL CONDITIONS

Years	**1-4**	**5-8**	**9-12**	**13-16**	**17-20**
HV Tr	0.44%	0.44%	0.44%	0.44%	0.44%
MV Tr	0.57%	0.57%	0.57%	0.57%	0.57%
HV GIS	0.36%	0.13%	0.23%	0.30%	0.57%
MV GIS	0.36%	0.13%	0.23%	0.30%	0.57%
CB	0.16%	0.29%	0.29%	0.30%	0.41%
Cable	0.66%	0.66%	0.66%	0.66%	0.66%

TABLE II
COSTS (IN K$) AND TIME (IN DAYS) NEEDED TO UNDERTAKE OFFLINE M&I ACTIONS

	CM		**PM & IIM**		**Inspection**	
	Cost	Time	Cost	Time	Cost	Time
HV Tr	424	49	268	5	134	3
MV Tr	200	60	232	5	116	2
HV GIS	300	4	116	5	58	1
MV GIS	150	4	100	2	50	1
CB	20	5	-	-	-	-
Cable	2	1	-	-	-	-

This configuration supports high reliability levels, as single component outages should not result in unsupplied energy. In the case of double outages, we assume that load can be transferred to nearby networks (which are not explicitly modeled) with a probability of 80%. Additionally, when a component fails, there is a 5% probability that all downstream demand needs to be curtailed due to failures in automatic transfer operations in the low-voltage network (which is not explicitly modeled). In that case, demand is manually reconnected after 10 minutes. Supply interruptions are very costly, as they disrupt production processes downstream: the cost of the first 30 minutes of interruption is valued at 288 k$ per MW disconnected, whereas energy not supplied after that time period is valued at 200 k$ per MWh.

The system's entry point is at 110 kV, which is first stepped down to 12 kV by two 120-MVA transformers (HV-Tr). Six 40-MVA transformers (MV-Tr) reduce this voltage further to 4.2 kV where different loads are supplied. The network contains ten gas insulated switchgear (GIS) components, which consists of two 110-kV circuit breakers (HV-GIS) and eight 12-kV circuit breakers (MV-GIS). Additionally, the system includes thirty 4.2-kV circuit breakers (CB) and twelve 4.2-kV cables that connect the loads to this supply network.

We consider a 20-year simulation horizon where failures are realized on a daily basis following failure probabilities determined by their state of degradation. The failure rate of the GIS circuit breakers depends on the age of the component. Numerical values for different ages were obtained from a survey on GIS reliability conducted by CIGRE [32]. Similarly, failure rates for circuit breakers of different ages were obtained from another survey on reliability conducted by CIGRE [33]. However, because that survey was focused on high voltage components, the data was adjusted to meet the average failure rate of circuit breakers of the appropriate voltage level according to [34]. Failure rates for transformers and cables are assumed to be independent of the age of these equipment and were obtained from [35] for HV transformers, and from [34] for MV transformers and cables. Table I presents failure rates for each type of equipment at different ages. Note that degradation is calibrated to match these historical failure rates under nominal loading.

In the case of transformers and cables, their loading is used to compute acceleration factors that adjust their degradation speed. To do so, we first compute the steady-state temperature (neglecting fast variations) of these components based on their loading, as indicated in [36] for transformers and in [37], [38] for cables. Then, Eq. (7) is used to compute the thermal acceleration factor F_{it}^{T} for component i at time t, where B is a constant that depends on the component, Θ^{d} is the nominal design temperature, and Θ_{it} is the actual temperature [36], [38].

$$F_{it}^{T} = e^{\left(\frac{B}{\Theta^{d}+273} - \frac{B}{\Theta_{it}+273}\right)} \tag{7}$$

Since thermal failures represent only 10% of major transformer failures [35], these factors accelerate only 10% of degradation. Mathematically, this means that degradation increases in steps of $F_{it} = 1\% \cdot (0.9 + 0.1 \cdot F_{it}^{T})$ in Eq. (1) (where the degradation increases in 1% in every step when the loading/temperature is the nominal one). As no information is available regarding the relative importance of thermal failures in cables, we also apply a 10% factor for them.

B. Maintenance and Inspection Actions

Table II summarizes the cost and time required to carry out corrective maintenance, preventive maintenance, inspection-induced maintenance on each type of component. No planned offline M&I actions are undertaken on circuit breakers and cables.

The cost and time required to undertake maintenance actions triggered by inspections are assumed to be the same as those of preventive maintenance actions. Maintenance actions do not necessarily decrease degradation to 0%; instead, we consider that when a component is connected back in service, its (new) degradation state follows a uniform distribution between 0% and 20% (where 100% is the maximum degradation). Furthermore, we assume that human errors can be made when performing any type of maintenance and that they result in a 0.5% failure probability on the day the component is connected back into service after maintenance. This probability decays to zero after one day (i.e., $T = 1$ in Eq. (3)).

In addition to the offline M&I actions already described, the maintenance policy includes two types of online inspections. The first one costs $280 per component and is carried out on all the components except for circuit breakers and cables. The second one carries a cost of $15 and is performed on every component except for cables. The result of inspections is the observed degradation state, which follows a normal distribution with an expected value equal to the actual degradation state, and a standard deviation depending on the inspection action undertaken. This standard deviation is 1% for offline inspections, and increases to 5% and 8% for the first and second types of online inspections, respectively.

C. Maintenance Policy

To construct a detailed schedule of M&I actions over the simulation horizon, the maintenance policy specifies three steps that must be performed in the following order:

1) Schedule corrective maintenance of failed components as soon as possible.
2) Schedule maintenance of components whose degradation has exceeded the inspection threshold (x_3) as soon as possible.
3) Schedule preventive maintenance and inspection actions of components considering their frequency (x_1 and x_2) and the last time they were performed.

Furthermore, the following four rules must be respected:

1) Multiple M&I actions cannot be scheduled simultaneously on the same component.
2) Offline M&I actions cannot be scheduled on days when there are components out of service.
3) Offline M&I actions cannot be scheduled on a given equipment on the day when its redundant counterpart is connected back in service.
4) Preventive maintenance on each 110/12 kV transformer must be scheduled simultaneously with maintenance on 3 12/4.2 kV transformers and all the associated gas insulated switchgear.

The first rule ensures that there is enough time to perform each action, whereas the other rules aim to construct maintenance schedules that take advantage of the relations among components within the system. The second rule aims at ensuring adequate redundancy levels by forbidding to schedule offline M&I actions when other components are out of service. The third rule minimizes the consequences of failures due to human error. Finally, the last rule states that preventive maintenance of components must be grouped in a block-type fashion. This rule stems from the fact that carrying out preventive maintenance of a transformer or GIS on a one-by-one basis may require costly switching activities, incurring high fixed costs. However, a significant part of these fixed costs can be shared among various components if maintenance actions are carried out simultaneously over groups of components. Therefore, it is more efficient to carry out preventive maintenance actions on as many components as possible, which in this case correspond to half of them (due to redundancy levels). Note that the same concept could be utilized to implement an opportunistic maintenance strategy, based on what is proposed in [24]. In this strategy, prior to performing unplanned maintenance on a component (either IIM or corrective maintenance), the other ones would be inspected, and maintenance would be carried out "opportunistically" on them if the observed degradation exceeds a threshold similar to x_3, but lower. This threshold is less stringent than the normal threshold for IIM because conducting maintenance in this situation is less costly as a result of sharing fixed costs.

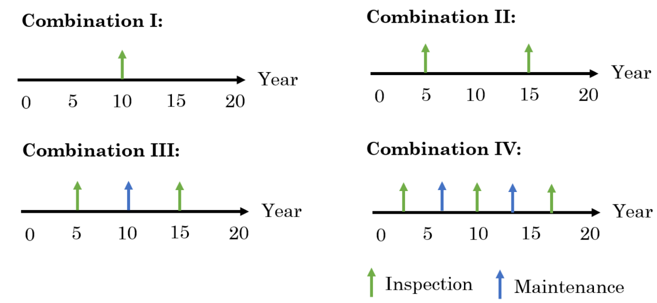

Fig. 5. Possible combinations of maintenance and inspection frequencies.

Three types of parameters are optimized to determine the minimum-cost maintenance policy, namely, the frequency of preventive maintenance actions, the frequency of inspections, and the thresholds for inspection results that trigger inspection-induced maintenance. x_1 is a scalar value that determines the frequency of preventive maintenance for the whole system. The scalar parameter x_2 determines the frequency of offline inspection actions for the whole system. We assume a constant frequency of six months for the first type of online inspections, and a constant frequency of three months for the second. x_3 is a vector consisting of three scalars, which are thresholds for each type of inspection. Note that, for a given inspection action, the same threshold is used on every component to determine IIM. Although these thresholds can take any value between 0% and 100%, we discretized the possible values in multiples of 10% to reduce the search space of the optimization.

Offline maintenance and inspection actions are expensive and can be performed only a few times over the 20-year simulation horizon. Fig. 5 shows four possible combinations of preventive maintenance and offline inspection frequencies (x_1 and x_2). The first two combinations do not consider preventive maintenance actions ($x_1 = 0$), while combinations III and IV include both offline inspections and preventive maintenance. These combinations constitute the discrete search space for x_1 and x_2. x_3 is tuned by the optimizer for every combination.

V. Results

Six sets of studies were performed to investigate the costs and benefits of alternative M&I strategies.

A. Base Case

The base case aims to select the policy parameters that minimize the expected total cost over the 20-year simulation horizon. In addition to the four candidate combinations of preventive maintenance and inspection frequencies (x_1 and x_2), two other cases are considered:

1) One where no offline M&I actions are performed and maintenance relies solely on online inspections.
2) Another one where corrective maintenance is the only type of M&I action performed.

TABLE III
COST (IN MILLION \$) OF DIFFERENT COMBINATIONS

	Combination I	II	III	IV
CMI	2.46	3.94	6.70	11.08
CCM	0.02	0.02	0.04	0.08
CENS	0.40	0.42	0.48	1.48
Total	**2.88**	**4.38**	**7.22**	**12.64**
CI	±0.02	±0.04	±0.02	±1.76
CVaR CENS	1.23	1.64	1.70	20.02

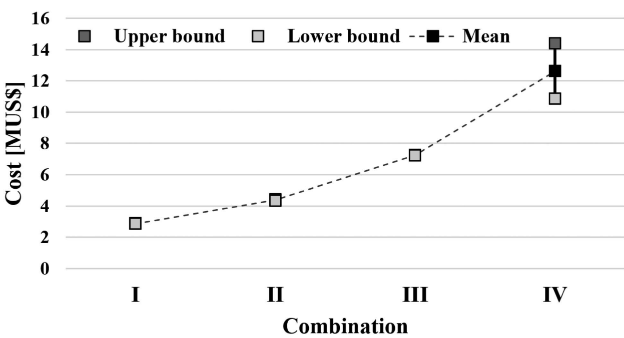

Fig. 6. Mean and the 95% confidence interval for the total cost of each combination. Notice that confidence intervals of combinations I-III are negligible.

The optimal policy parameters were obtained by carrying out 10,000 simulations spanning 20 years with a daily resolution. Combination I produces the optimal set of maintenance and offline inspection frequencies. Interestingly, combination I considers only one offline inspection and no preventive maintenance over the system's lifespan. Additionally, the optimal threshold for IIM (x_3) is found to be 70% for offline inspections, and 80% for both types of online inspections.

Table III compares the various costs of the four combinations when the optimal inspection thresholds are set. It features the following rows:

1) CMI: The expected cost of planned maintenance and inspection actions (excluding corrective maintenance).
2) CCM: The expected cost of corrective maintenance actions.
3) CENS: The expected cost of energy not supplied.
4) Total: Total expected cost, equal to the sum of CMI, CCM and CENS.
5) CI: 95% confidence interval for the expected total cost.
6) CVaR CENS: The $\text{CVaR}_{95\%}$ of the unsupplied demand cost, computed as the average of the 5% highest-cost scenarios.

The mean cost of the M&I plan increases with the number of offline M&I actions, mainly due to the costs of performing these actions. It is clear that combination I presents the lowest mean cost, and it is the alternative that considers fewer offline M&I actions. Fig. 6 illustrates the effect of the uncertainty associated with Monte Carlo simulations, and shows that combination I is definitely the best alternative, as the upper bound of its 95% confidence interval is lower than the lower bound of the other combinations.

TABLE IV
COST (IN MILLION \$) OF TWO M&I PLANS WITHOUT OFFLINE M&I ACTIONS

	Online inspections	Only CM
CMI	0.98	0.00
CCM	0.02	0.42
CENS	0.42	2.22
Total	**1.42**	**2.64**
CI	±0.02	±0.42
CVaR CENS	1.32	11.02

Interestingly, the results show that maintenance actions decrease system reliability. This is because components are maintained regardless of their true condition, which reduces redundancy while offline M&I actions are carried out, and creates the possibility of human error.

Table IV presents the results with two other M&I plans. In the first one, only online inspections are performed. In the second one, there are no preventive maintenance or inspection actions but only corrective maintenance.

Relying solely on online inspection actions, disregarding both offline inspections and preventive maintenance is the most cost-effective approach. Notice that the expected energy not supplied associated with that plan is similar to that of combination I, but its total cost is lower since there are no costly offline inspections. The plan that disregards M&I actions (except for corrective maintenance) has the highest cost of energy not supplied. Moreover, the conditional expectation of the costs in the worst cases is also very high, as expressed by the $\text{CVaR}_{95\%}$. Most of the reduction in unsupplied energy can be achieved with online inspections and no offline M&I actions. This shows that, albeit less accurate, online inspections are more cost-effective because they are less expensive and can be carried out more regularly, and thus provide more opportunities to detect high degradation states. Since offline M&I actions are carried out only a few times over the 20-year horizon, their benefits are limited.

B. Implementation of Advanced Monitoring Techniques

In this case study, we assume that condition monitoring devices provide access to continuous and precise estimations of the actual state of degradation of the components. Albeit unrealistic, this provides an estimate of the maximum benefit that condition-based maintenance strategies could achieve. In this case, the M&I plan must be entirely based on the use of condition monitoring data, and no other maintenance or inspection actions can be performed. Only one threshold has to be selected and, once a component reaches that threshold, inspection-induced maintenance is carried out.

Optimizing the threshold for continuous monitoring IIM gives a value of 80%. Based on 5,000 simulations assuming this threshold, the expected costs of planned M&I actions is

TABLE V
COSTS (IN MILLION $) OF A STRATEGY TO HEDGE AGAINST DOUBLE OUTAGES

	Combination			
	I	**II**	**III**	**IV**
CMI	2.46	3.94	6.70	11.08
CCM	0.02	0.02	0.04	0.08
CENS	0.34	0.36	0.42	0.54
Total	**2.82**	**4.32**	**7.16**	**11.70**
CI	± 0.02	± 0.02	± 0.02	± 0.02
CVaR CENS	1.18	1.18	1.58	1.88

TABLE VI
COST (IN MILLION $) OF DIFFERENT COMBINATIONS WHEN THERE IS NO REDUNDANCY ON CABLES

	Combination			
	I	**II**	**III**	**IV**
CMI	2.36	3.84	6.60	10.98
CCM	0.04	0.04	0.06	0.10
CENS	420.30	416.98	432.64	431.94
Total	**422.68**	**420.84**	**439.30**	**443.00**
CI	± 10.80	± 10.26	± 11.22	± 11.54
CVaR CENS	1426.51	1366.76	1491.39	1555.50

800 k$, the expected cost of corrective maintenance is 4 k$, and the cost of energy not supplied is 20 k$, with a $\mathrm{CVaR}_{95\%}$ of 340 k$. These add up to a total cost of 820 k$, within a confidence interval of ± 20 k$. There are various reasons for this important cost reduction compared to the base case. First, there are no unnecessary M&I actions as maintenance is carried out only when needed, and discrete inspection actions are not necessary since there is continuous and precise information about the condition of the assets. Second, since components are maintained before they fail, unplanned outages are rare. Finally, components are taken out of service only when it helps avoid unplanned outages, thus reducing redundancy only when necessary.

It is vital to notice that the proposed model is also able to analyze the case of imperfect monitoring. In this non-ideal case, monitoring data is used to trigger further inspection actions, ultimately determining if maintenance is required. Therefore, the observed state from online monitoring would present noise with a given variance higher than that of physical inspections. In this way, the maintenance policy would involve two threshold parameters, the one where monitoring data triggers inspections, and another where inspections trigger maintenance actions.

C. Strategies to Hedge Against Double Outages

A component can fail while the component for which it provides redundancy is unavailable due to an offline M&I action. Different approaches can be followed to minimize the consequence of such a scenario. This case study aims to compare the existing strategy with one where spare components are used during outages. Hence, we assume that a spare component is connected immediately after a component is taken out of service, thereby restoring the redundancy level. We also assume that there is only one spare component per type of asset in the system. This strategy to hedge against double outages is beneficial for transformers because their corrective maintenance actions last several weeks.

Table V shows that there are no major differences between this case and the base case. This is because double outages on redundant components are very unlikely. Therefore, implementing a strategy to hedge against them does not produce significant benefits.

D. Different Network Designs

In this case, we study the system's performance when there is no redundancy in the 4.2 kV cables. This helps understand and quantify the true benefits of having redundant infrastructure on those components. These benefits can then be compared with the costs of equipment and space associated with this redundancy. Apart from removing the redundant cables and their circuit breakers, we modify the remaining cables' capacities, so they are loaded at 80% of their capacity under normal conditions. Inspection-induced maintenance can no longer be carried out on cables, or any of their circuit breakers, since this would lead to energy not supplied.

Table VI shows the costs obtained for different maintenance combinations when there is no redundancy in cables. The total cost under any combination is much higher than for the base case and is mainly driven by the energy not supplied. When there is redundancy, unplanned outages of cables or circuit breakers produce a short demand disconnection of downstream demand on 5% of the cases. However, when there is no redundancy, failures produce supply losses that can span several days. These results highlight the high value of the reliability provided by redundancy.

E. The Effect of Human Hazards

This case study analyzes the effects of human hazards on the optimal maintenance policy. If a member of personnel suffers an accident while performing maintenance, the system may be shut down for a period of time, which can entail important economic consequences. In this way, depending on the risk associated with maintenance actions, it may be optimal to reduce their frequency in order to minimize the probability of human hazards. It is critical to understand that this case study only considers the economic consequences in terms of loss of supply and in no way intends to assign an economic value to personnel's health.

In this case, we consider that human hazards can occur with a probability of 0.01% when performing maintenance actions and that the system has to be shut down for three days if a human hazard occurs. Table VII presents the most important results regarding the costs of each combination of maintenance and inspection frequencies. It is clear that the most significant difference with the base case is the presence of higher levels of

TABLE VII
COST (IN MILLION $) OF DIFFERENT COMBINATIONS WHEN HUMAN HAZARDS ARE CONSIDERED

	Combination			
	I	**II**	**III**	**IV**
CMI	2.46	3.93	6.70	11.07
CCM	0.02	0.02	0.05	0.08
CENS	1.83	1.84	6.18	7.56
Total	**4.31**	**5.79**	**12.93**	**18.71**
CI	±1.22	±1.24	±2.49	±3.61
CVaR CENS	29.72	29.93	115.53	141.56

TABLE VIII
COST (IN MILLION $) OF DIFFERENT COMBINATIONS WHEN THE LOW-VOLTAGE NETWORK IS MODELED IN DETAIL

	Combination			
	I	**II**	**III**	**IV**
CMI	8.32	9.79	12.56	16.93
CCM	0.05	0.05	0.09	0.11
CENS	0.57	0.62	0.72	0.79
Total	**8.94**	**10.46**	**13.37**	**17.83**
CI	±0.02	±0.05	±0.05	±0.03
CVaR CENS	1.51	2.28	2.45	2.43

unsupplied energy. Notice that ENS is lower when there are no scheduled time-based maintenance actions (combinations I and II). When maintenance is carried out irrespective of the state of degradation of components (combinations III and IV), the cost of ENS increases significantly. Therefore, the probability of human hazards has the effect of making time-based maintenance even less attractive, emphasizing the benefits of strategies based on inspection actions. Additionally, this case study illustrates the flexibility of the proposed approach, as it is able to deal straightforwardly with high-impact low-probability events, which are usually challenging to incorporate in mathematical models.

F. Larger-Scale System

In this subsection, we expand the network under analysis to demonstrate the proposed method's scalability. We do so by explicitly modeling the low-voltage network, which comprises 180 transformers that reduce the voltage from 4.2 to 0.4 kV and the associated 180 circuit breakers at the 4.2 kV level. These new components are also connected following the spot-network design approach, so every component has physical redundancy, which means that two redundant elements must fail in order to produce demand curtailment. For the new components, we only consider regular online inspections, the associated IIM, and corrective maintenance, without scheduling preventive maintenance or offline inspections.

The results for this case are presented in Table VIII. The differences in cost that arise when considering these new components are mostly justified by the greater number of inspection actions that need to be carried out. Additionally, having more components increases the probability of undergoing failures, which explains the increase in energy not supplied. However, the main conclusions about the optimal maintenance policy are not modified. Combination I remains the alternative with minimum cost. It is important to notice that as the new components do not require planned offline M&I actions, their effects on the total cost do not change significantly throughout the different combinations. Note that, although these additions significantly increase the number of elements in the system, the proposed method is able to determine the optimal maintenance plan, as one advantage of our simulation-based approach is that the computation time scales linearly with the number of elements.

VI. CONCLUSION

This paper proposes an approach to the development of maintenance policies for power supply systems that optimize the balance between costs and benefits. The proposed approach relies on a stochastic optimization-via-simulation model. Policy parameters are set in the first stage and define M&I plans that are simulated in the second stage under a comprehensive array of failure scenarios. Hence, the second stage informs the first stage about the reliability performance associated with the policy parameters chosen. The first stage then adjusts these parameters iteratively to identify the optimal set of policy parameters.

Numerical results on the power supply system of an industrial facility demonstrate that offline inspections can displace preventive maintenance actions. Such actions can indeed be undertaken more effectively in a corrective manner when triggered by inspection results or after a failure occurs. In turn, online, low-cost, and frequent inspections can provide more benefits than more costly and sparse offline inspections.

Our results also demonstrates that asset redundancy achieves a higher reliability value than maintenance plans, confirming that network reliability is to a significant extent supported by its redundant structure. Although M&I actions can support system reliability, physical redundancy is paramount and should be considered the primary measure to supply critical loads in a reliable fashion. The case studies also demonstrate that, in networks with redundant links, the availability of spare equipment, which are stored offline and connected when the primary equipment is being maintained to avoid losing redundancy, may be of limited benefit.

These findings are relevant for industrial loads since they demonstrate the effects of M&I plans on supply continuity along with addressing real-life concerns such as the importance of human errors, the value of online inspections, and the role of network redundancy versus that of M&I plans in the provision of reliability.

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