Maintenance Strategy Optimization for Complex Power Systems Susceptible to Maintenance Delays and Operational Dynamics

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***Abstract*—Maintenance is a necessity for most multicomponent systems, but its benefits are often accompanied by considerable costs. However, with the appropriate number of maintenance teams and a sufficiently tuned maintenance strategy, optimal system performance is attainable. Given system complexities and operational uncertainties, identifying the optimal maintenance strategy is a challenge. A robust computational framework, therefore, is proposed to alleviate these difficulties. The framework is particularly suited to systems with uncertainties in the use of spares during maintenance interventions, and where these spares are characterized by delayed availability. It is provided with a series of generally applicable multistate models that adequately define component behavior under various maintenance strategies. System operation is reconstructed from these models using an efficient hybrid load-flow and event-driven Monte Carlo simulation. The simulation's novelty stems from its ability to intuitively implement complex strategies involving multiple contrasting maintenance regimes. This framework is used to identify the optimal maintenance strategies for a hydroelectric power plant and the IEEE-24 RTS. In each case, the sensitivity of the optimal solution to cost level variations is investigated via a procedure requiring a single reliability evaluation, thereby reducing the computational costs significantly. The results show the usefulness of the framework as a rational decision-support tool in the maintenance of multicomponent multistate systems.**

***Index Terms*—Complex system, maintenance optimization, Monte Carlo simulation, multistate system, uncertainty.**

Notations

$\boldsymbol{A} - \boldsymbol{B}$	Elements in $\boldsymbol{A}$ but not in $\boldsymbol{B}$.
$\lceil a \rceil$	Smallest integer greater than a.
$\min(\boldsymbol{A})$	Least element of set/vector $\boldsymbol{A}$.
$\min(\boldsymbol{A}, b)$	Least element of $\boldsymbol{A}$ greater than b.
$Exp(a)$	Exponential distribution with rate $1/a$.
$U(a, b)$	Uniform distribution with bounds on a, b.
$LogN(a, b)$	Log-normal distribution with mean a, std. b.
$Wb(a, c)$	Weibull distribution with scale parameter a and shape parameter, c.
$Gu(a, b)$	Gumbel distribution with mean a, std. b.
$G(a, b)$	Gamma distribution with shape parameter a and scale parameter, b.
$u \sim [0, 1]$	Uniform random number between 0 and 1.
$[a, b]$	Maint. strategy based on regimes a and b.
$\mathrm{numel}(\boldsymbol{A})$	Number of elements in set/vector $\boldsymbol{A}$.

Abbreviations

APM	Awaiting preventive maintenance state.
CM	Corrective maintenance state.
EENS	Expected energy not supplied.
$(\mathrm{EENS})_{\mathrm{eff}}$	total EENS.
D	Diagnosis state.
F	Failed state.
I	Idle state.
PF	Partial failure state.
PM	Preventive maintenance state.
S	Shutdown state.
W	Working state.

Nomenclature

p_i	Probability of spares for CM of component i.
q_i	Probability of spares for PM of component i.
t_{pm}	Preventive maintenance duration.
k_i	Proportion of t_{pm} spent before spares request.
Λ_i	Minimum threshold load for component i.
ω	Number of maintenance groups.
n_{t_j}	Total number of teams in group j.
n_{1_j}	Number of CM teams in group j.
n_{2_j}	Number of PM teams in group j.
$\boldsymbol{n}^*$	Combination of maintenance teams
m_j	Total number of components in group j.
M	Total number of maintainable components.
M'	Total number of system nodes.
T_m	Mission time.
$\boldsymbol{T}_i$	Transition matrix for component i.
N	Number of Monte Carlo samples.
$\mathbb{N}$	Set of possible maintenance team combinations
$N_i^{\{\mathrm{cm}\}}$	Number of CM actions on component i.
$N_i^{\{\mathrm{pm}\}}$	Number of PM actions on component i.
$t_i^{\{\mathrm{cm}\}}$	Time spent by component i in CM.
$t_i^{\{\mathrm{pm}\}}$	Time spent by component i in PM.
$s_i^{\{\mathrm{cm}\}}$	Number of CM spares used for component i.

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$s_i^{\{\mathrm{pm}\}}$ Number of spares used in PM of component i.
$\mu_i^{\{\mathrm{cm}\}}$ CM suspension indicator for component i.
$\mu_i^{\{\mathrm{pm}\}}$ PM suspension indicator for component i.
t_s Current simulation time.
x Current state.
y_{next} Next transition state.
t_{next} Next transition time.
y_m Next maintenance state.
y' Next failure state of a component in APM.
t' Maximum lifetime of a component in APM.
t_{spent} Time spent in PM before maint. suspension.
t_{spare} Spares delay time.
t_{rem} Remaining lifetime of a component.
$\theta_j^{\{\mathrm{cm}\}}$ Set of components repaired by group j.
$\theta_j^{\{\mathrm{pm}\}}$ Set of components assigned to group j for PM.
θ_j $\left(\theta_j^{\{\mathrm{cm}\}} \cup \theta_j^{\{\mathrm{pm}\}}\right)$.
$\lambda_j^{\{\mathrm{cm}\}}$ Number of busy CM teams from group j.
$\lambda_j^{\{\mathrm{pm}\}}$ Number of busy PM teams from group j.
$\mathbf{\Pi}$ Matrix defining the number of maint. teams.
φ Shared/dedicated maintenance indicator.
h_1 Set of components in CM queue.
h_2 Set of components in PM queue.
h_{1f} Final content of h_1 after normalization.
h_{2f} Final content of h_2 after normalization.

I. Introduction

OWING to the rapid growth in human population and the proliferation of new electrical-energy-driven technologies, the demand for sustainable electricity is on a steady rise. Coupled with a competitive market, the electrical power operator is under increasing pressure to deliver an adequate, safe, affordable, and uninterrupted supply. They, however, are constrained by the impossibility to continuously operate the system without outages, consequent of component failure, and maintenance. To minimize the impact of these outages on consumer satisfaction, the maintenance strategy adopted should be robust, meet operator expectation, extend the life of the system, and be carefully executed [1], [2]. From an operator perspective, a robust strategy is one that ensures the maximum system throughput and keeps the operating cost to a minimum. In addition to its impact on system performance, maintenance accounts for a significant proportion of the total operating cost of power systems. It, therefore, to a significant extent, defines the revenue generated and the overall investment sustainability. In summary, the principles of modern maintenance engineering do not only require meeting technical and operational goals, but achieving them through the most cost effective means. This constraint dictates, maintenance follow a strategy imposing minimum system output loss and at the least possible cost.

A. Maintenance Strategy Optimization

In the most general sense, maintenance can be optimized against various reliability and performance indices. The indices used depend on the application and the goal of the analyst. For instance, in nuclear and other safety-critical systems, failure probability and recovery likelihood are the most frequently used indices. However, regardless of the application and the indices used, the goal is finding the optimum balance between costs and benefits, while not ignoring any important system constraints [2]. This process involves comparing the monetary equivalent of the benefits to the costs incurred in their attainment. A limiting factor, therefore, would be the convertibility to monetary gains of these benefits. Consequently, cost minimization has been the subject of many maintenance optimization models [1], [3]–[12]. While some of these models consider the system as a single unit (for instance, [1], [6], [13]), many are enhanced for multicomponent systems. With respect to implementation effort, multicomponent models are more demanding, due to the presence of multiple system dynamics and structural complexities. Notwithstanding, various researchers have successfully implemented maintenance optimization models on multicomponent systems [3]–[5], [8]–[11]. A comprehensive review and historical overview can be found in [14]–[16].

The cost of maintaining a system constitutes various parameters, varying according to the external dynamics surrounding the system and the intrinsic properties of its building block. Prominent among these are the reliability and maintainability of components, cost of spares, labor cost, and the frequency and duration of PM actions. An accurate model, therefore, accounts for all of these parameters. With a few exceptions focusing on reliability-centered maintenance [5], [8] or maintenance contract assessment [17], most of the models are dedicated to determining either the optimal PM schedule, inspection, or component replacement intervals. Often, they are hinged on the assumption that there are sufficient maintenance teams to accomplish maintenance functions [4]–[9], [11], [17] and delays imposed by logistic and administrative constraints are usually ignored [3]–[9], [11], [17]. Instantaneous PM or inspection is another assumption frequently invoked [3], [4], [9], [11], [13]. While these assumptions are reasonable for some systems, they may be completely unrealistic for many, a notable instance being a system with large maintenance durations and operated under limited maintenance team conditions. These large durations, normally due to logistic or human resource constraints, affect system performance negatively. They also render the cost and number of spares used worth considering, a factor many maintenance optimization models have ignored.

When the possibility of maintenance interruptions exists, constraints on the states of components during periods of maintenance suspension become important. A component's maintenance is suspended if it requires spares which availability is delayed or if the maintenance team is reassigned to a more critical component. During suspensions, the component may either be put back into operation (assuming it is only partially failed or under PM) or kept out of operation until maintenance is completed. The careful scheduling of these maintenance actions may also mitigate their effect on throughput losses. This is the case especially for planned PM and CM of partially failed components. Hence, there is the need for an optimization framework that derives the combination of procedures (maintenance strategy) minimizing system losses, as well as the maintenance cost. Maintenance strategy here refers to a set of procedures specifying the following.

1) The number of maintenance teams employed and how they are assigned to components.
2) Whether or not PM and CM should be carried out by the same team.
3) Whether PM interventions and CM of partially failed components should consider the state of the system or a relevant subsystem.
4) What happens to a component when its maintenance is suspended.

Significant strides have already been made toward maintenance strategy optimization in the presence of some of these, including other dynamic considerations like ageing, imperfect, and condition-based maintenance [3], [4], [18], [19]. However, the techniques proposed in these works are suited mainly to binary-state systems. An approach considering all the constraints in question and in a multistate multicomponent environment is yet to emerge. In this work, a simulation framework that can be used to identify the optimal maintenance strategy for a multistate system prone to the range of possible operational dynamics listed is proposed. A detailed account of its theoretical and modeling principles is provided, thereby setting the tone for its wide applicability.

B. *Advantages of the Proposed Approach*

The dependability of the optimal solution obtained from any maintenance strategy optimization scheme is determined by the accuracy of its system performance measures. This, in turn, is influenced by the suitability to the system of the reliability modeling technique employed. These modeling techniques fall into one of two broad categories: analytical and dynamic reliability models. The former are inapplicable to certain reliability problems, especially those involving complex maintenance strategies and other dynamic considerations. When forced to suit such problems, the resulting models are often oversimplified to an extent that compromises the credibility of the outcome. In fact, most of the limitations of the existing maintenance optimization models discussed in the preceding section are associated with analytical models.

Dynamic reliability models, on the other hand, possess sufficient flexibility to model the dynamic considerations and uncertainties that normally characterize the operation of realistic systems. Stochastic Petri Nets [20], stochastic hybrid systems [21], and Monte Carlo simulation [3], [22]–[24] are the most popular in this category. Stochastic Petri Nets, however, require the enumeration of the entire state space of the system, which makes them infeasible for complex multistate systems, even of moderate size. They also suffer a serious setback when the system can undergo non-Markovian transitions, in which case Tuffin *et al.* [25] recommend simulation. Stochastic hybrid systems are an emerging modeling formalism with promising prospects for dynamic reliability modeling. They are built around the Markov reward model of the system when solicited for problems involving performance optimization or system operating cost minimization [21]. Consequently, like stochastic Petri Nets, they are intractable for complex multistate systems, due to their susceptibility to the state explosion conundrum. In addition, they proceed by translating the dynamic reliability problem into a set of differential equations, which closed-form solution, in some cases, may be difficult to obtain analytically. Some researchers [26] have even had to resort to a Monte Carlo simulation approach to solving these differential equations. Given the structural complexity of most of the power systems and their multistate attributes, Monte Carlo simulation, therefore, remains the most feasible approach, regardless of its higher computational intensity.

However, most of the Monte Carlo simulation algorithms [23], [27], [28] require prior knowledge of the system's structure function or its path or cut set, which for complex multistate systems is tedious. In [22], a simple load-flow-based simulation approach, applicable to any system configuration, was introduced. It allows the simulation of a multistate system without the need to define its structure function, path, or cut sets. Notably, it enables the replication of realistic system operating principles, like shutdown and restart of components. These shutdown events can be as a result of the unavailability of another component or loading restrictions imposed on the components themselves. When dealing with maintainable systems, it is vital to consider this form of functional interdependence between components, as the failure and PM of most of components depend on the effective time spent in operation. Most of the reliability and performance analysis approaches disregard this feature because it is either impossible or difficult to determine the actual flow through system components. We adapt this modeling approach to systems with limited maintenance teams, prone to maintenance delays and other operational uncertainties. The modified approach is a credible pathway via which system performance indices relevant to the maintenance model are derived, without making unrealistic assumptions.

Appreciating that most of the power systems exhibit multistate characteristics, each system component is modeled as a semi-Markov stochastic process. The multistate model is modified to incorporate additional stochasticity induced by the operational dynamics surrounding the system. Thus, the resultant component model is also a translation of system dynamics from the system to the component level. This model simplifies the simulation procedure, rendering it more intuitive and generally applicable. Most importantly, the simulation procedure supports the complex scenario where various components follow different maintenance strategies, another limitation of the existing models.

The remainder of this work is organized as follows: Section II is dedicated to defining key terms, presenting a general overview of the problem under consideration, the proposed cost model, and a description of the solution procedure. In Section III, a background to the component and system models is presented. The simulation algorithm and details on how components are modeled to account for various system dynamics are also described here. Section IV presents two case studies, illustrating the application of the models developed to realistic systems. Finally, in Section V, a conclusion is drawn on the proposed framework, with insights on its applicability.

II. Problem Formulation

Consider a multicomponent system of an arbitrary structure, composed of either binary-state components, multistate components, or both. These components can undergo CM when in a degraded state and PM, which interval is determined by the effective time spent in operation since the last maintenance action (i.e., periods when the component is unavailable do not count). State transition times of components may be constant or follow any probability distribution. On entering a degraded state, a component is added to the maintenance queue and its repair process follows two stages: a diagnosis stage and a stage dedicated to actual repairs. At the end of diagnosis, the maintenance team may proceed to the second stage or initiate a spares request, if spares are required. The probability of the latter happening is p_i, where i, a positive integer arbitrarily assigned, is the index of the component in the system. There is a delay between initiation of spares request and their delivery, which may vary from component to component and may again follow any probability distribution. Like CM, PM is prone to interruptions at a probability q_i. This is normally realized after an average time $k_i t_{\mathrm{pm}} \mid 0 < k_i < 1$, t_{pm} being the component's expected PM duration, and k_i being the proportion of this time to elapse before the need for spares is realized. While the crew awaits the spares, they can be assigned to another job, if there are no other idle maintenance teams.

At the system level, components are arranged into ω maintenance groups, and each group maintained by $n_{t_j} \mid j = 1, 2, \ldots, \omega$ maintenance teams. Under dedicated maintenance, n_{t_j} is expressed in the form $(n_{1_j}, n_{2_j}) \mid n_{1_j} + n_{2_j} = n_{t_j}$, where n_{1_j} is the number of teams dedicated to CM, and n_{2_j} is the number of teams dedicated to PM. It is assumed that each of these n_{t_j} teams has the expertise to maintain any of the m_j components in group j. Maintenance is outsourced, and its cost constitutes three parts: a fixed cost per unit time per maintenance team, a fixed cost per maintenance call, and a fixed cost per unit time of actual maintenance service. There are no penalty costs on the system operator for failing to meet demand, but consumers only pay for the quantity of output supplied. The lost revenue accrued, with the total maintenance cost over a period, provides a measure of the performance of the system for that period. It is desired to find the maintenance strategy and the value of $n_{t_j} \forall j \in \{1, 2, \ldots, \omega\}$, ensuring optimum system performance. The objective of the optimization procedure is the minimization of system maintenance cost, as well as the cost incurred from unmet demand. A given strategy, therefore, is optimal if it minimizes the total cost.

There are a few attributes of the system described that pose some challenges. From a modeling point of view, the fact that the system could be multistate and of any architecture disqualifies most of the existing system reliability evaluation techniques (see Section I-B). Similarly, the limited number of maintenance teams, the uncertainties associated with the need for spares to complete a maintenance action, and the delays in the availability of these spares present a serious planning and scheduling dilemma. For instance, if the maintenance crew knew that every PM action would require spares, they would place a spares request in advance. Conversely, they could carry with them a few spares in anticipation, but this would be applicable only to nonbulky components, since there is a limit to how much could be carried. The need, therefore, for an optimal maintenance strategy cannot be overemphasized.

A. Definition of Key Terms

1) *Expected Output-Not-Supplied*: A measure of the expected amount by which the actual system output deviates from its expected level, within a given period, T_m. This quantity, in power systems, is known as the *EENS*, and it accounts for the periods the system performance curve is below the load curve. If $Y(t)$ and $Y_d(t)$, respectively, denote the instantaneous system output and demand, then, for a demand-driven system (i.e., $Y(t) \le Y_d(t)$)

$$\mathrm{EENS} = \int_0^{T_m} \left(Y_d(t) - Y(t)\right) dt. \tag{1}$$

For a given system reliability problem, $Y_d(t)$ is normally known, and $Y(t)$ is computed from the system reliability analysis outcome. When obtained via Monte Carlo simulation, $Y(t)$ is defined by a collection of discrete sets of system performance levels as a function of time. Therefore, the discrete form of (1) should be used to compute the system EENS. Given that $Y(t)$ is random, the EENS is computed as the average of the performance deficiencies of all the samples of $Y(t)$. For N Monte Carlo samples of $Y(t)$, let the ith sample contain n_i performance-level transitions, $y_{ij} = Y_d(t) - Y(t)$ at the jth transition, and $t = t_{ij} \mid 0 \le t_{ij} \le T_m$, the corresponding transition time; then

$$\begin{aligned} \mathrm{EENS} &= \frac{Y_0}{N} \\ Y_0 &= \sum_{i=1}^{N} \left(y_{in_i}\left(T_m - t_{in_i}\right) + Y_1\right) \\ Y_1 &= \sum_{j=2}^{n_i} y_{i(j-1)}\left(t_{ij} - t_{i(j-1)}\right) \end{aligned} \tag{2}$$

where y_{in_i} and t_{in_i} are, respectively, the final performance level and last transition time of sample i. Alternatively, if instead of $Y(t)$ and $Y_d(t)$, only the possible system performance and demand levels with their corresponding occurrence probabilities are known, the EENS is computed through a different approach. Let the system exist in n distinct output levels as defined by vector $\mathbf{C}$, with probability of occurrence within the period, T_m, defined by vector $\mathbf{P}$. The expected performance deviation per unit time, β, and EENS are

$$\beta = \sum_{j=1}^{\alpha} (j, \mathbf{P}_d)\, \beta_0^{\{j\}}$$
$$\beta_0^{\{j\}} = \sum_{i=1}^{n} \max\left((j, \mathbf{C}_d) - (i, \mathbf{C}), 0\right)(i, \mathbf{P})$$
$$\text{EENS} = T_m \beta \tag{3}$$

where α is the number of possible demand levels, $\mathbf{C}_d$ is the vector defining these levels, and $\mathbf{P}_d$ is the vector specifying their corresponding probabilities of occurrence. For systems like power distribution networks with multiple load points, the effective EENS, $(\text{EENS})_{\text{eff}}$, is given by the sum of the EENS at all the load points.

2) *Shared Maintenance:* In this maintenance strategy, the same team is assigned to perform both PM and CM on a component or a group of components.

3) *Dedicated Maintenance:* Unlike shared maintenance, separate teams carry out PM and CM on the same group of components. This implies that a failed or a component due for preventive maintenance remains unattended if its dedicated maintenance team is unavailable.

B. Cost Model

The resultant effect of component failure, maintenance strategy, and operational dynamics on the system is expressed in terms of the expected total loss, L, incurred. Assuming zero inflation, its components are expressed as follows:

1) Loss, L_1, due to lost output, which in turn is due to system outages, consequent of component failure, and maintenance. If C_0 is the cost of a unit output, L_1 is expressed as

$$L_1 = C_0\, (\text{EENS})_{\text{eff}}\,. \tag{4}$$

For commercial power systems, EENS is in kWh and C_0 is the cost of a kWh (e.g., in £/kWh).

2) Fixed maintenance cost, L_2, emanating from fixed wages for maintenance personnel. If each team of group j is paid r_j units of currency per unit time, L_2 is given by

$$L_2 = T_m \sum_{j=1}^{\omega} r_j n_{t_j}\,. \tag{5}$$

3) Total cost, L_3, associated with the fixed cost per maintenance action. This cost is normally associated with transportation of crew, contribution to offset purchasing cost of tools, or both. If m_c is the cost per maintenance action and $N_i^{\{\text{cm}\}}$ and $N_i^{\{\text{pm}\}}$ are, respectively, the number of successful CM and PM actions for component i, L_3 is given by

$$L_3 = \sum_{i=1}^{M} m_c \left(N_i^{\{\text{cm}\}} + N_i^{\{\text{pm}\}}\right)$$
$$M = \sum_{j=1}^{\omega} m_j \tag{6}$$

where M is the number of maintainable components of the system. When expressed in closed form, (6) takes the form

$$L_3 = \{m_c\}_{1\times M}\{N_i^{\{\text{cm}\}}, N_i^{\{\text{pm}\}}\}_{M\times 2}\{1\}_{2\times 1} \mid i = 1, 2, \ldots, M. \tag{7}$$

4) Cost, L_4, of maintaining system components, a function of the time spent by each component in maintenance and the cost per unit time of maintenance. If $C_i^{\{\text{cm}\}}$ and $C_i^{\{\text{pm}\}}$ are, respectively, the costs of CM and PM of component i per unit time, $t_i^{\{\text{cm}\}}$ and $t_i^{\{\text{pm}\}}$, its total time spent in CM and PM, L_4 is expressed as

$$L_4 = \sum_{i=1}^{M} \left(C_i^{\{\text{cm}\}} t_i^{\{\text{cm}\}} + C_i^{\{\text{pm}\}} t_i^{\{\text{pm}\}}\right). \tag{8}$$

In closed form, (8) is given by

$$L_4 = \{1\}_{1\times M}\boldsymbol{l}\{1\}_{2\times 1}$$
$$\boldsymbol{l} = \left(\left\{C_i^{\{\text{cm}\}}, C_i^{\{\text{pm}\}}\right\}_{M\times 2} \circ \left\{t_i^{\{\text{cm}\}}, t_i^{\{\text{pm}\}}\right\}_{M\times 2}\right). \tag{9}$$

The "$\circ$" operator denotes elementwise multiplication of two matrices.

5) Cost, L_5, of spares used in maintaining system components. For most of the systems, on average, the spares used during PM are minor and cheaper when compared to those used in CM. Let $s_i^{\{\text{cm}\}}$ and $s_i^{\{\text{pm}\}}$ be the number of spares used in CM and PM of component i, respectively. If their corresponding unit costs are $C_{s_i}^{\{\text{cm}\}}$ and $C_{s_i}^{\{\text{pm}\}}$, respectively, then L_5 is expressed as

$$L_5 = \sum_{i=1}^{M} \left(C_{s_i}^{\{\text{cm}\}} s_i^{\{\text{cm}\}} + C_{s_i}^{\{\text{pm}\}} s_i^{\{\text{pm}\}}\right) \tag{10}$$

which in closed form condenses to

$$L_5 = \{1\}_{1\times M}\boldsymbol{l}\{1\}_{2\times 1}$$
$$\boldsymbol{l} = \left(\left\{C_{s_i}^{\{\text{cm}\}}, C_{s_i}^{\{\text{pm}\}}\right\}_{M\times 2} \circ \left\{s_i^{\{\text{cm}\}}, s_i^{\{\text{pm}\}}\right\}_{M\times 2}\right). \tag{11}$$

The overall system lost revenue, L, is given by

$$L = \sum_{i=1}^{5} L_i. \tag{12}$$

Normally, the nominal system output and the various costs are known. Determination of L, therefore, effectively reduces to the task of estimating $(\mathrm{EENS})_{\mathrm{eff}}$, $\{N_i^{\{\mathrm{cm}\}}, N_i^{\{\mathrm{pm}\}}\}_{M\times 2}$, $\{t_i^{\{\mathrm{cm}\}}, t_i^{\{\mathrm{pm}\}}\}_{M\times 2}$, and $\{s_i^{\{\mathrm{cm}\}}, s_i^{\{\mathrm{pm}\}}\}_{M\times 2}$ via reliability evaluation. These parameters are a function of the failure and maintenance events of the system components and are, therefore, random. As a consequence, their mean/expected values are used in calculating the system lost revenue, L.

If the system reliability and performance indices, for strategy k, are represented by the function $R(\boldsymbol{n}^*, k)$, and the set of costs by C, then the system loss function can be expressed in the form $L(C, R(\boldsymbol{n}^*, k))$. With $R(\boldsymbol{n}^*, k)$ known for all possible strategies, the optimal maintenance strategy can be identified and its sensitivity to variations in cost levels investigated without the need for multiple simulations.

C. *Proposed Maintenance Regimes*

Depending on the type of maintenance strategy in use, different system performance outcomes are possible, even with the same number of maintenance teams. For instance, in a series-connected system, it may seem reasonable to postpone PM until system failure. In such a scenario, PM and CM actions are performed concurrently. Ideally, this should result in reduced system downtime and subsequent improvements in performance. This is normally the case if PM actions are frequent and require large times, or if some components are not easily accessible, such that their maintenance inflicts significant throughput losses on the system. However, postponing a component's PM may increase its likelihood of failure and bring with it additional costs. These costs are incurred from spares used, longer system down times, and higher maintenance intervention costs, as CM durations normally are longer. In addition, more than one maintenance team may be required for efficient implementation of this strategy, since there may be multiple components requiring maintenance intervention when the system fails. On the downside, the teams are idle while the system is in operation but continue to receive salaries as the maintenance contract demands. A similar argument can be proffered for CM of partially failed components, if, in spite of the failure, system performance remains above a certain threshold. This procedure, however, may be counterproductive if component interdependencies exist in the system, such that a degraded component affects the operation of healthy ones. Therefore, even for a system, it is difficult to determine whether the procedure yields the most cost effective solution without a detailed reliability analysis. In summary, the optimality of a given strategy depends, among other factors (cost levels, for instance), on the topology of the system and the nontopological functional relationships between its components.

Generally, the following regimes may be considered when deciding the promptness of PM and major CM of partially failed components.

1) Maintenance can be carried out at any time. The time of intervention depends only on the availability of maintenance teams.
2) Maintenance is carried out only when system output is nominal.
3) Maintenance is carried out only when a component is not in operation. This may coincide with the unavailability of the entire system or the unavailability of the subsystem to which it belongs.

When the maintenance of a component is interrupted due to delays in the availability of spares, two possible scenarios ensue.

4) The component remains shutdown until spares are made available. In this case, there are no risks of incurring additional costs from failures. However, the maintenance team may be assigned to another task during the wait, and there will be revenue losses as the system operates below its nominal performance level.
5) The component is put back into operation, in which case it continues to perform its normal function. This results in no loss of system output, provided that it does not fail.

D. *Solution Sequence*

The regimes highlighted in Section II-C can be arranged into two groups. Regimes 1–3 define the promptness of maintenance actions, and regimes 4 and 5 define the status of a component during maintenance interruptions. Each system component may be subjected to a combination of regimes, one from each group, giving rise to six possible maintenance strategies. Depending on the dynamics surrounding the operation of the system, additional strategies are applicable. For instance, on the basis of division of labor, PM and CM interventions could be shared or dedicated. This would lead to a total of 12 possible strategies, if considered. The corresponding component and system models are then derived for each of these strategies in preparation for system optimization.

The optimization procedure follows a two-stage approach. In the first stage, the optimal maintenance strategy is identified by analyzing each system model, with no restriction on the number of maintenance teams. For each case, the performance function, L, is determined, and the optimal strategy is identified as the one yielding the least value of L. The second stage searches for the optimal number of maintenance teams using this strategy. Here, the system is reanalyzed for various values of n_{t_j} in shared policies and various combinations of n_{1_j} and n_{2_j} in dedicated policies. Given that a component can undergo only one maintenance intervention at any instance, each n_{t_j} is bounded by $(0, m_j)$ and $\sum_{j=1}^{\omega} n_{t_j} \leq M$. In dedicated policies, both n_{1_j} and n_{2_j} are bounded by $(0, m_j)$, with the additional condition $n_{1_j} + n_{2_j} \leq m_j$. Additional constraints may be imposed on the number of maintenance teams in each group, depending on the maintenance strategy and certain requirements set by the operator. For example, if two maintenance groups i and j have at least one component in common, then $n_{t_i} + n_{t_j} \leq |\, \theta_i \cup \theta_j \,|$. The operator, under economic constraints, may also impose bounds that are less than the limits already defined on the maintenance team size. Let $\boldsymbol{n}^* \mid \boldsymbol{n}^* = \{n_{t_1}, n_{t_2}, \ldots, n_{t_\omega}\}$ represent a combination of maintenance teams and $\mathbb{N} \mid \mathbb{N} = \{\boldsymbol{n}_1^*, \boldsymbol{n}_2^*, \ldots, \boldsymbol{n}_\phi^*\}$ the set of all possible maintenance team combinations, with ϕ denoting their total. Deriving $\mathbb{N}$ entails obtaining, first, the set defined by the number of components in each group, such that $\mathbb{N} = \{1, 2, \ldots, m_1\} \times \{1, 2, \ldots, m_2\} \times$

$\ldots \times \{1, 2, \ldots, m_\omega\}$ and $\phi = \prod_{j=1}^{w} m_j$. Any combinations not satisfying the operator and maintenance-strategy-imposed constraints are removed

$$\left(L_{\max}, k_{\text{opt}}\right) = \min\left(\left\{L\left(C, R\left(\infty, k\right)\right)\right\}^{\mho}\right)$$
$$k = 1, 2, \ldots, \mho \quad k_{\text{opt}} \leq \mho \tag{13}$$
$$\left(L_{\min}, \boldsymbol{n}^{*}_{\text{opt}}\right) = \min\left(\left\{L\left(C, R\left(\boldsymbol{n}^{*}_{j}, k_{\text{opt}}\right)\right)\right\}^{\phi}\right)$$
$$j = 1, 2, \ldots, \phi \quad \boldsymbol{n}^{*}_{\text{opt}} \in \mathbb{N} \quad L_{\min} \leq L_{\max}. \tag{14}$$

The optimal solution, therefore, is defined by the triplet $\left(L_{\min}, \boldsymbol{n}^{*}_{\text{opt}}, k_{\text{opt}}\right)$, where $L_{\min}$, $\boldsymbol{n}^{*}_{\text{opt}}$, and k_{opt} are, respectively, the minimum system loss, the optimal maintenance team size combination, and the optimal strategy. If $R(\infty, k)$ represents the reliability/performance indices of the system under maintenance strategy k with no restrictions on the number of maintenance teams, and $\mho$ the number of strategies, (13) and (14) summarize the optimization procedure. $R(\infty, k)$ is obtained by setting the number of teams in each maintenance group to the number of components in that group. For this, components belonging to multiple groups are assumed to belong to the group with the least cost per maintenance team.

Large systems often result in a large number of candidate solutions. In such cases, it is advised to exploit smart optimization techniques such as genetic algorithm [3], [4], [9] and particle swarm optimization [5]. These, however, have not been considered, as the objective here is to provide a clear insight on the component and system modeling procedures.

III. System Reliability and Performance Analysis

In this section, a brief description of the component and system modeling procedures is presented, with details on the algorithms invoked in the reliability evaluation process. To ensure simplicity and maintain focus on the modeling procedures, a perfect maintenance situation is assumed. It is, however, worthwhile noting that this is in no way limiting, as the framework can easily be extended to imperfect maintenance scenarios.

A. Component and System Representation

The multistate model introduced in [22] is adopted to define the behavior of each system component. This model takes cognizance of the various parameters required for the complete representation of attributes of a component. It accounts for the component's possible state transitions, their associated probability distributions, the performance level associated with each state, and any load restrictions imposed on the component.

The system is modeled as a graph, in which nodes represent the components and demand points of the system, and edges represent their physical links. Define the connectivity of the graph to be a square adjacency matrix, conditioned to incorporate the efficiency of the physical links. Efficient algorithms were proposed in [22] to deduce the system flow equations from this matrix. These equations, a function of the flow properties of the components, are in a format suitable for direct computation with the interior-point algorithm [29]. Given a system state vector, the actual flow through every node can be determined by updating the flow equation matrices and applying the interior-point algorithm. In addition to the advantages already outlined in Section I-B, the matrix representation of the system structure makes the procedure easily implementable on a digital computer. Readers are referred to [22] for the details on the multistate component model and the flow equations.

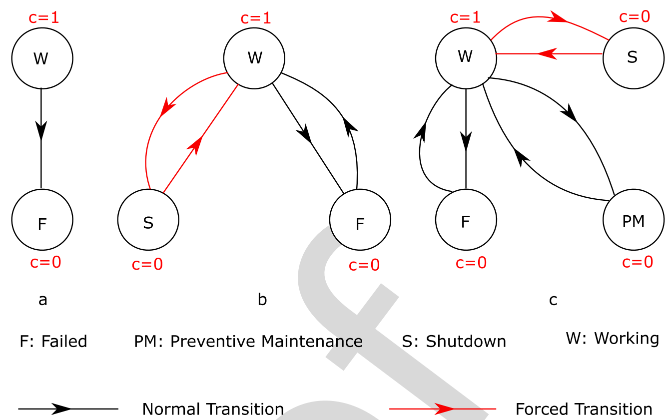


Fig. 1. State-space representation of a binary-state component under various maintenance scenarios.

B. Maintenance Modeling of Components

Consider a hypothetical series system, composed of binary-state components (components naturally existing in only two states) with capacity, c, equal to 1 when working, and 0 otherwise. The effects of repairs and PM on the state space of each system component, without maintenance delays, uncertainties, and maintenance suspensions, are first presented. The resulting models are later modified and generalized for multistate components in systems prone to maintenance delays and operational dynamics.

The following maintenance scenarios are considered.

1) Each component of the system is nonrepairable [see Fig. 1(a)].
2) A component can be repaired when failed [see Fig. 1(b)].
3) A component can undergo preventive, as well as CM [see Fig. 1(c)].

Unlike the nonrepairable case, a failed component is subject to repairs in scenarios 2 and 3. This is indicated by a transition from state F to state W in Fig. 1(b) and (c). While the component is in operation, other components of the system may fail. Given that a series system is unavailable with the unavailability of at least one of its components, available components are unavoidably taken out of operation during repairs of failed components. A third state, S, is, therefore, introduced to account for this dependent unavailability of the operating component, as shown in Fig. 1(b) and (c). The component remains in this state until all failed components are repaired, following which, it is restarted and restored. A fourth state, PM, is incorporated in Fig. 1(c) to represent the period the component is in PM.

One can easily deduce that the transitions from W to F and W to PM are competing, which is due to the perfect maintenance assumption used. Since PM and repairs make the component

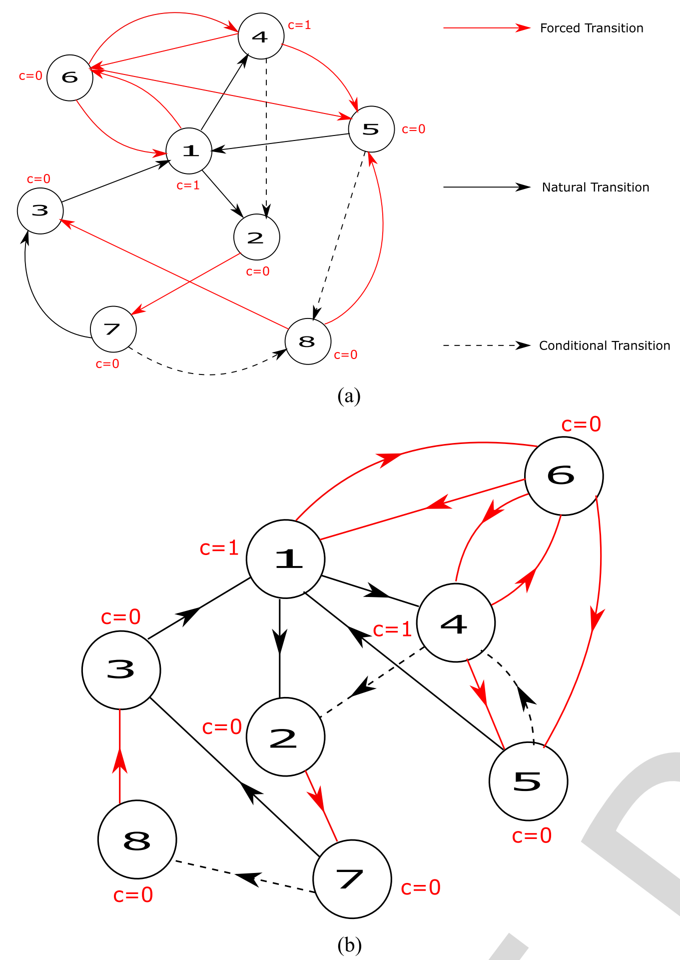


Fig. 2. Repairable binary-state component under maintenance delays and operational uncertainties. (a) Kept out of operation during spares delays. (b) Returned into operation during spares delays.

as good as new, any pending failures are eliminated after PM, and any scheduled PM is reset after repairs. An as good or bad as old assumption would have been implemented by replacing the transition from W to PM with a forced transition. This, however, is outside the scope of this work. It is also clear that none of the three scenarios discussed considers the effects of external factors on component state transitions. For instance, there are no delays in the commencement of maintenance, and the maintenance process once initiated suffers no obstructions or suspensions. This, however, is not the case for many practical systems.

Suppose the series system is replaced with the system described in Section II, such that there are more components than maintenance teams. To model such a case, four additional states are introduced in the state-space diagram in Fig. 1(c), as shown in Fig. 2. A description of the state designations and a summary of the transitions depicted are presented in Tables I and II, respectively. Fig. 2 also reveals that component state transitions can be classified as either *natural* (*normal*), *forced*, or *conditional*. Natural transitions occur randomly and depend only on their associated distributions. Forced transitions occur purely as a consequence of events outside the component boundary, and their distributions are unknown. Conditional transitions, on the other hand, have a known distribution, but are assigned a lower priority and only occur on fulfillment of a predefined condition or a set of conditions. In the transition matrix, $\mathbf{T}_i$, of the component, conditional and forced transitions are indicated by ∞ in their relevant positions (see [22]). Unlike natural transitions in which the next state of a component depends only on its current state, the next state of a component under a forced transition may also depend on its previous state. For this reason, a set of special procedures are defined to execute them during system simulation.

TABLE I
COMPONENT STATE ASSIGNMENT

State	Designation	Description
1	Working	Component operates at required capacity level.
2	Failed	Component is failed and CM is yet to commence; $c = 0$.
3	CM	Component is under repairs; $c = 0$.
4	APM	Component is due for PM but maintenance is yet to commence; $c > 0$.
5	PM	PM in progress; $c = 0$.
6	Shutdown	Component not failed but taken out of operation; $c = 0$.
7	Diagnosis	Failure is being diagnosed by maintenance team; $c = 0$.
8	Idle	Diagnosis is complete but the maintenance team is waiting for spares, to resume maintenance. Required only if delays in availability of spares is modeled; $c = 0$.

TABLE II
DESCRIPTION OF STATE TRANSITIONS

Transition	Description	Transition	Description
1-2	Component Failure	7-3	Fault Diagnosis Duration
1-4	PM Interval	5-1	PM Duration
3-1	CM Duration	4-2	Failure of component whilst awaiting PM team
2-7	Forcing Diagnosis; determined by availability of maintenance team	5-8	spares needed during PM; determined by probability of spares being used
8-5	spares are available and PM resumes; determined by availability of PM team	8-3	spares are available and PM resumes; determined by availability of CM team
7-8	Spares needed during CM; determined by probability of spares being used	1-6	Shutdown event like failure of system or another component
6-1,6-4	Component Restart; suggests correction of event leading to shutdown	6-5	PM during shutdown; determined by availability of maintenance team and whether previous state of component was APM (state 4)
4-6	Shutdown event whilst component is due for PM	4-5	Forcing PM; determined by availability of maintenance team and spares
5-4	PM interruption due to spares delay		

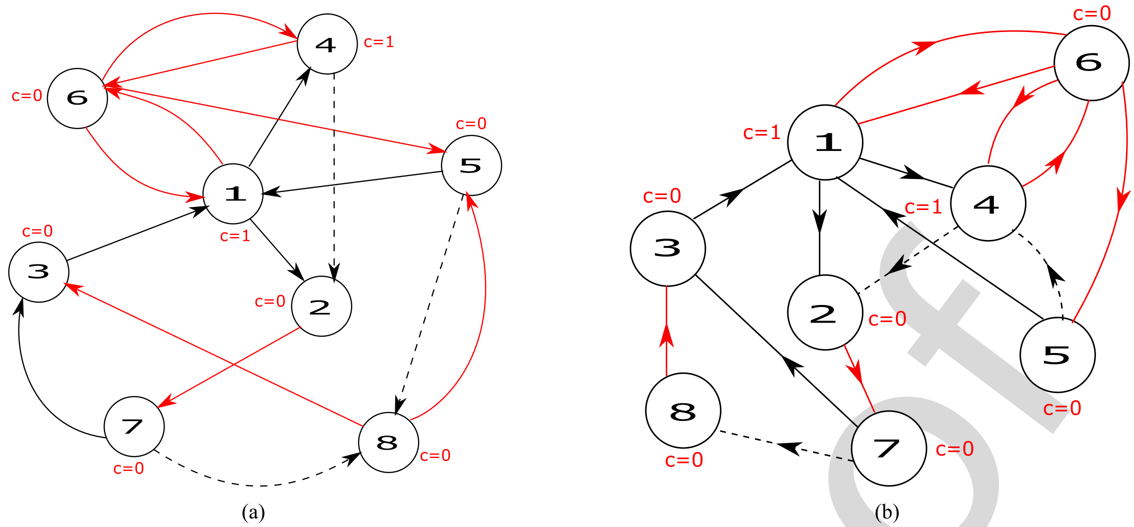


Fig. 3. Repairable binary-state component under the assumption "maintenance only when component is unavailable." (a) Kept out of operation during spares delays. (b) Returned into operation during spares delays.

The component models presented in Fig. 2 are based on the assumption that PM can be carried out at any time or only when system performance is nominal. However, if PM is carried out only when a component is out of service, the models are as presented in Fig. 3. The difference between the two sets of models is the absence of the transition from state 4 to state 5 in Fig. 3. They share the same modeling principles, as well as the designations in Tables I and II.

Multistate component modeling under maintenance delays follows a similar approach. The models in Figs. 2 and 3 can easily be generalized for multistate components by defining one idle state (if components are kept out of operation during spares delay), a "Diagnosis" state (where necessary), and one CM state for each repairable failure mode, as shown in Fig. 4. In Fig. 4, states 4 and 5 are a PF mode and its corresponding CM state, respectively. States 9 and 10 are additional "Diagnosis" and "Idle" states, respectively, for the PF mode. All the other states and transitions retain their designations and meanings, as defined in Tables I and II.

C. Determining Component Transition Parameters

A system's reliability analysis by Monte Carlo simulation entails the sequential generation of the transition states and times of its components, with a view to replicating its actual operation. In a multistate environment, a component's next transition state, y_{next}, and time, t_{next}, are determined by which of the possible transitions from its current state, x, occurs first. Given its transition matrix, all the possible transitions from state x are sampled, and the sampled times are stored in a register, $\boldsymbol{Ttimes}$. The transition corresponding to the least element of this register gives the next state of the component, while the next transition time is given by the sum of the least element and the current simulation time, t_s. In the event of multiple transitions satisfying this condition, one of them is randomly selected.

The sampling procedure described is pretty straightforward and directly applicable to most of the multistate models. However, when PM is modeled as a competing transition with failures, and in the presence of limited maintenance teams, a slight modification to the procedure is required. For instance, if a working component is due for PM (state 4 in Figs. 2 and 3), and for some reason, there is a significant delay, it may fail (transition from state 4 to state 2) before the commencement of maintenance. The elapsed time depends on what the failure time would be assuming the component was not subject to PM. Therefore, if on application of the procedure, the component is found to survive till PM is due (i.e., its next state is APM), its next failure state y' and the maximum period t' it will survive before failure are also determined. This procedure is summarized by Algorithm 1 (see Fig. 5).

1) Accounting for Non-Markovian Transitions: Algorithm 1 (see Fig. 5) is only applicable to Markovian transitions (i.e., the next state of a component depends only on its current state). A second procedure, therefore, is required to implement the *forced* and *conditional* transitions. The transitions to and from shutdown, except those from shutdown to CM, PM, or Diagnosis (see Figs. 2–4), can be implemented by the shutdown and restart procedure described in [22]. The remaining conditional and forced transitions are dependent on the availability of maintenance teams or spares, where required. For these, a maintenance-forcing procedure, hinged on the assumption that the component is already assigned to an available maintenance team, is proposed.

When a component makes a transition to a new state, its next transition parameters are automatically derived, using Algorithm 1. However, for the reasons already stated, this algorithm cannot derive forced maintenance transition parameters. The component's next maintenance state, y_m, from the new state is, therefore, manually determined from its transition matrix. With correct modeling according to the models proposed in Section III-B, each failure mode will have at most one

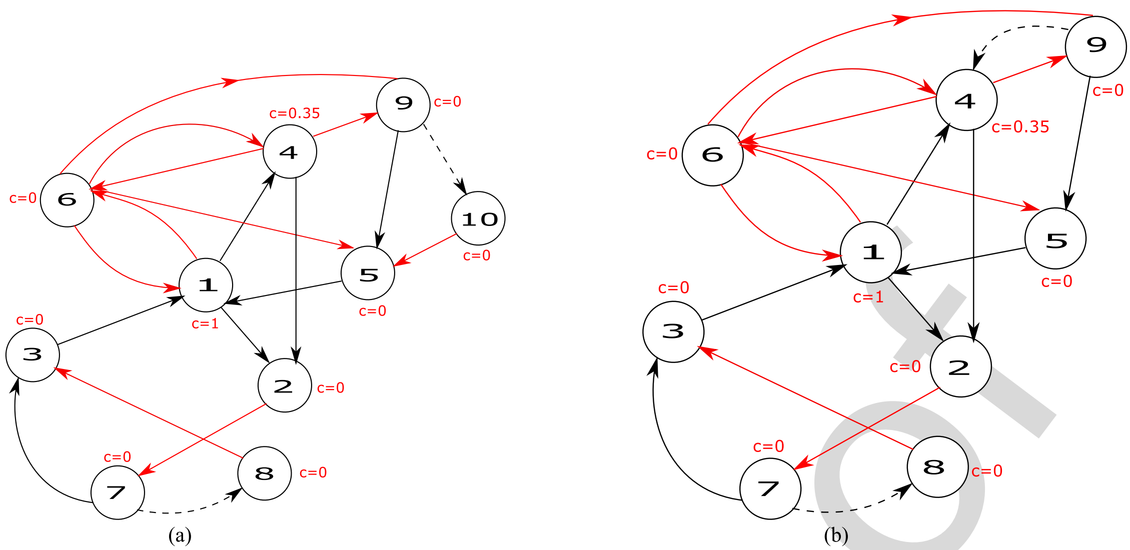


Fig. 4. Repairable multistate component under maintenance delays and operational uncertainties. (a) Kept out of operation during spares delays. (b) Returned into operation during spares delays.

Require: x and t_s

function SAMPLE(x)
  $\boldsymbol{J}$ ←set of possible transitions from state x
  $\boldsymbol{f}$ ←set of corresponding distributions
  k ←Number of elements in $\boldsymbol{J}$
  for n ←1 to k **do** ▷ Loop over possible transitions
    $(n, \boldsymbol{Ttimes})$ ←Sample from $(n, \boldsymbol{f})$
  end for
  $t_{sample} \leftarrow min(\boldsymbol{Ttimes})$ ▷ get earliest time
  $\boldsymbol{p}$ ←transitions corresponding to t_{sample}
  if $numel(\boldsymbol{p}) > 1$ **then** ▷ if multiple transitions
    $u \sim [0, 1]$ ▷ generate uniform random number
    $index \leftarrow (\lceil u * numel(\boldsymbol{p}) \rceil, \boldsymbol{p})$
  else
    $index \leftarrow \boldsymbol{p}$
  end if
  $y_{next} \leftarrow (index, \boldsymbol{J})$ ▷ get next state
  if y_{next} is APM **then** ▷ survives till PM is due
    $t'_{sample} \leftarrow min\,(\boldsymbol{Ttimes}, t_{sample})$
    y' ←state corresponding to t'_{sample}
    $t' \leftarrow t'_{sample} - t_{sample}$
  end if
  return $(y_{next}, t_{sample}, y', t')$
end function
$t_{next} \leftarrow t_{sample} + t_s$

Fig. 5. Algorithm 1: Sampling procedure for transition parameters of a multistate component with PM, under a limited maintenance team scenario.

maintenance state (CM or Diagnosis) associated with it. The component is added to the CM queue if y_m exists. If, on the other hand, the new state is APM, the transition parameters of the component are not obtained by another application of Algorithm 1. They are determined from y' and t', obtained when the algorithm was applied when the component entered the Working state (state W). In this case, y_m is the only PM state, and the component is added to the PM queue.

In the most general case, y_m could either be Diagnosis, CM, or PM. To force maintenance, y_m is made the current state of the component, and Algorithm 1 is applied to determine its next transition parameters. It is deducible from the component models presented in Figs. 2–4 that a component in Diagnosis (state 7) can either undergo a normal transition to CM (state 3) or a conditional transition to the Idle state (state 8). However, the sampling algorithm always yields the normal transition. Given that the conditional transition to Idle state occurs only if spares are required, a uniform random number, u, between 0 and 1 is generated and compared to the probability, p_i, of spares being needed to complete the maintenance. The Idle state (state 8) is made the next transition state if $u \leq p_i$, and the transition time yielded by the sampling algorithm is retained. In the case of repair from a PF mode, such that the component is returned into operation during spares delay [see states 4 and 9 in Fig. 4(b)], the PF mode is made the next state, and $\mu_i^{\{\text{cm}\}}$ is assigned the value 1. $\mu_i^{\{\text{cm}\}}$ is an indicator function that takes the value 1 when CM is suspended, and 0 otherwise. The component is removed from the maintenance queue until the spares requested are made available

$$\begin{aligned} t_{\text{spent}} &= k_i t_{\text{pm}} \\ t_{\text{next}} &= t_s + (1 - k_i)\, t_{\text{pm}} \\ &= t_s + \left(\frac{1}{k_i} - 1\right) t_{\text{spent}}. \end{aligned} \qquad (15)$$

Similarly, a component in PM (state 5 in Figs. 2 and 3) can either return to the Working state (state 1), go to the Idle state (state 8), or return to its previous state if it should be kept in operation while awaiting spares. Like CM, any of the last two outcomes is determined by the probability, q_i, of spares being needed to complete PM. The next transition time if spares are

Require: p_i, q_i, k_i, $s_i^{\{cm\}}$, $s_i^{\{pm\}}$, t_s, y_m, $\mu_i^{\{cm\}}$, $\mu_i^{\{pm\}}$

1: **function** FORCEMAINTENANCE(i, $input$)
2: $x \leftarrow y_m$ ▷ Force transition
3: $(y_{next}, t_{sample}, \sim, \sim) \leftarrow$SAMPLE($x$)
4: **if** x is PM **then** ▷ In preventive maintenance
5: **if** $\mu_i^{\{pm\}} \leftarrow 1$ **then** ▷ From suspension
6: $t_{sample} \leftarrow (\frac{1}{k_i} - 1)t_{spent}$
7: $\mu_i^{\{pm\}} \leftarrow 0$ ▷ Reset indicator
8: **else if** $u \sim [0,1] \leq q_i$ **then** ▷ Spares needed?
9: $s_i^{\{pm\}} \leftarrow s_i^{\{pm\}} + 1$ ▷ add PM spares used
10: $t_{sample} \leftarrow k_i t_{sample}$
11: $x_{prev} \leftarrow$ previous state
12: **if** $\mathbf{T}_i(x, x_{prev}) \neq 0$ **then** ▷ If to restart
13: $y_{next} \leftarrow x_{prev}$
14: **else**
15: $y_{next} \leftarrow$'Idle' state linked to x
16: **end if**
17: $\mu_i^{\{pm\}} \leftarrow 1$ ▷ Set indicator
18: **end if**
19: **else if** x is Diagnosis **then**
20: **if** $\mu_i^{\{cm\}} \leftarrow 1$ **then** ▷ From suspension
21: $x \leftarrow$ CM state connected to x
22: $\mu_i^{\{cm\}} \leftarrow 0$ ▷ Reset indicator
23: $(y_{next}, t_{sample}, \sim, \sim) \leftarrow$SAMPLE($x$)
24: **else if** $u \sim [0,1] \leq p_i$ **then**
25: $s_i^{\{cm\}} \leftarrow s_i^{\{cm\}} + 1$ ▷ add CM spares used
26: *call lines 12 to 16*
27: $\mu_i^{\{cm\}} \leftarrow 1$ ▷ Set indicator
28: **end if**
29: **end if**
30: $t_{next} \leftarrow t_{sample} + t_s$
31: **return** (y_{next}, t_{next}, $s_i^{\{cm\}}$, $s_i^{\{pm\}}$, $\mu_i^{\{cm\}}$, $\mu_i^{\{pm\}}$)
32: **end function**

Fig. 6. Algorithm 2: Procedure for forcing maintenance.

required is given by $t_s + k_i t_{\text{pm}}$, where t_{pm} is the PM duration yielded by Algorithm 1, and k_i is its proportion spent before the maintenance team realizes that spares are required. When PM is suspended, the component is removed from the maintenance queue, and $\mu_i^{\{\text{pm}\}}$, its indicator function for PM suspension, set to value 1. On PM resumption, the expected duration of the remainder of the maintenance exercise is $(1 - k_i)\, t_{\text{pm}}$. To avoid storing too many variables during simulation, this period is expressed in terms of t_{spent}, the time spent by the component in PM before maintenance suspension. t_{spent} is computed from the saved transition history of the component, and the next transition time, t_{next}, is derived as in (15). The maintenance-forcing procedure described above is summarized by Algorithm 2 (see Fig. 6).

D. Maintenance Strategy Implementation

Algorithm 2 assumes that the component has already been assigned an available maintenance team. However, with multiple components requiring maintenance intervention, maintenance team assignment follows the maintenance strategy in use. Let h_1 and h_2 be the sets of components requiring CM and PM, respectively, $\mathbf{\Pi} = \{n_{1_j}, n_{2_j}\}_{\omega \times 2} \mid j = 1, 2, \ldots, \omega$ be the matrix defining the number of CM and PM teams in each maintenance group, and $\boldsymbol{\varphi} = \{\varphi_j\}_{\omega \times 1}$ be an indicator vector, in which elements are matched to the rows of $\mathbf{\Pi}$

$$\varphi_j = \begin{cases} 1, & \text{If maintenance group j is shared} \\ 0, & \text{Otherwise.} \end{cases} \tag{16}$$

Each indicator element specifies whether its corresponding maintenance group practices shared or dedicated maintenance, as defined by (16).

Given the assumption of a component being as good as new after PM or CM and the additional constraint that the former is carried out only on the perfect component, the condition $h_1 \cap h_2 = \emptyset$ is imposed. Therefore, prior to maintenance team assignment, all the elements of $h_1 \cap h_2$ are removed from h_2 (i.e., $h_2 = h_2 - (h_1 \cap h_2)$ or simply $h_2 = h_2 - h_1$). Depending on the maintenance strategy, additional components may be removed from h_1 and h_2. For instance, if Ω is the set of components in the Shutdown state, η_1, the set of components repairable only while in the Shutdown state, and η_2, the set of components which PM is initiated only when in Shutdown, then $h_1 = (h_1 - \eta_1) \cup (\Omega \cap \eta_1)$ and $h_2 = (h_2 - \eta_2) \cup (\Omega \cap \eta_2)$. Similarly, let δ_1 be the set of components repairable only while system performance is nominal, and δ_2 be the set for which PM is initiated only at nominal system performance. If system performance is below nominal at maintenance team assignment, $h_1 = h_1 - \delta_1$ and $h_2 = h_2 - \delta_2$. Note that η_1 applies to partially failed components only.

With h_{1f} and h_{2f} representing the final contents of h_1 and h_2, respectively, the first maintenance group is considered. Its assigned components in the maintenance queue are ranked according to the predefined priority rule, and the top-ranked component is assigned to the first available team in the group. As a consequence, the number of available teams and the number of ranked components reduce by 1 each. The procedure is repeated until all the ranked components have been assigned or until there are no available maintenance teams in the group. At this stage, h_{1f} and h_{2f} are updated accordingly, and the next maintenance group considered if $h_{1f} \cup h_{2f} \neq \emptyset$. This recursive procedure continues until all the maintenance groups have been covered.

Let $\theta_j^{\{\text{cm}\}}$ be the set of components assigned to maintenance group j for CM and $\theta_j^{\{\text{pm}\}}$ be the set assigned for PM. If $\lambda_j^{\{\text{cm}\}}$ and $\lambda_j^{\{\text{pm}\}}$ are the numbers of unavailable teams from group j for CM and PM, respectively, Algorithm 3 (see Fig. 7) summarizes the maintenance strategy implementation procedure. Line 10 accounts for the case when components maintained only while system performance is nominal are removed from the queue following the deviation from nominal performance. This normally is a consequence of either PM or CM of a partially failed component of a higher rank in the queue.

Require: $(h_{1f} \cup h_{2f}) \neq \emptyset$, h_1, h_2

1: **for** $j \leftarrow 1$ to ω **do** ▷ Loop over maintenance groups
2: **if** $\varphi_j > 0$ **then** ▷ If maintenance is shared
3: $Teams \leftarrow \mathbf{\Pi}(j,1) + \mathbf{\Pi}(j,2) - \left(\lambda_j^{\{cm\}} + \lambda_j^{\{pm\}}\right)$
4: $X_{comp} \leftarrow \left(h_{1f} \cap \theta_j^{\{cm\}}\right) \cup \left(h_{2f} \cap \theta_j^{\{pm\}}\right)$
5: **while** $Teams > 0$ **and** $X_{comp} \neq \emptyset$ **do**
6: $i \leftarrow$top ranked component
7: FORCEMAINTENANCE(i, *input*)
8: $Teams \leftarrow Teams - 1$
9: $X_{comp} \leftarrow X_{comp} - i$ ▷ remove component
10: *adjust* X_{comp} *if necessary*
11: **end while**
12: **else**
13: $\boldsymbol{H} \leftarrow \{h_{1f}, h_{2f}\}$
14: $\boldsymbol{G} \leftarrow \{\theta_j^{\{cm\}}, \theta_j^{\{pm\}}\}$
15: $\boldsymbol{I} \leftarrow \{\lambda_j^{\{cm\}}, \lambda_j^{\{pm\}}\}$
16: **for** $k \leftarrow 1$ to 2 **do**
17: $X_{comp} \leftarrow (k, \boldsymbol{H}) \cap (k, \boldsymbol{G})$
18: $Teams \leftarrow \mathbf{\Pi}(j,k) - (k, \boldsymbol{I})$
19: *call lines 5 to 11*
20: **end for**
21: **end if**
22: *Remove assigned components from* h_{1f} *and* h_{2f}
23: **if** $(h_{1f} \cup h_{2f}) \leftarrow \emptyset$ **then**
24: **break**
25: **end if**
26: **end for**
27: *Remove assigned components from* h_1 *and* h_2

Fig. 7. Algorithm 3: Procedure for maintenance strategy implementation during simulation.

E. Simulation Procedure

A discrete-event simulation model is proposed to replicate the behavior of the system. Starting with components in their initial states, the initial performance level of the system is computed and recorded, following which the next transition parameters of each component are sampled, and the simulation progresses to the earliest transition time. At this time, the current state of the appropriate component making the transition is updated, its new state is recorded as a function of time, its next transition parameters are sampled, and the next simulation time is determined. This procedure is repeated for subsequent transitions until the mission time is exceeded. For every transition resulting in a change in the flow properties of a component, the output of the system is computed and recorded as a function of time. The relevant reliability and performance indices are determined from the saved component transition and system output histories.

Let $\boldsymbol{\tau}$ be the vector of next transition times of nodes (components and output points) and $\boldsymbol{\tau}_{\text{spare}}$ be the vector holding the availability times of component spares. If M' is the total number of system nodes, the simulation procedure is summarized as follows.

1) Initialize the system in preparation for simulation. This involves the following:
   a) initialization of registers to save the current flow properties of nodes, transition history of components, and the performance histories of output nodes;
   b) setting the required number of simulations, Nsamples, and mission time, T_m.
2) Set $t_s = 0$, $s_i^{\{\text{cm}\}} = s_i^{\{\text{pm}\}} = \mu_i^{\{\text{cm}\}} = \mu_i^{\{\text{pm}\}} = 0 \forall i \in \{1, 2, \ldots, M'\}$, $h_1 = h_2 = \emptyset$, $\boldsymbol{\tau} = \boldsymbol{\tau}_{\text{spare}} = \{\infty\}^{M'}$.
3) Save the initial states of components.
4) Compute the initial performance level of all the output nodes and save as a function of t_s.
5) Sample the next transition parameters (y_{next} and t_{next}) of nodes, update $\boldsymbol{\tau}$, and set $t_s = \min(\boldsymbol{\tau})$.
6) Check for nodes with next transition time equal to t_s. For each node, i,
   a) effect the required transition;
   b) with the exception of the case when the new state is APM, Idle, or PF given its previous state is Diagnosis, sample its next transition parameters and determine y_m, where applicable. Update h_1 or h_2 if y_m exists, set $\mu_i^{\{\text{cm}\}}$ and $\mu_i^{\{\text{pm}\}}$ to 0, and go to Step (g);
   c) if the new state is APM, $y_{\text{next}} = y'$, $t_{\text{next}} = t' + t_s$, y_m is set to the PM state, and h_2 is updated. However, h_2 is not updated if the node is returning from PM, as the transition depicts a maintenance suspension. In this case, $t_{\text{next}} = t_{\text{rem}} + t_s$, where t_{rem} is the remaining life of the component prior to its maintenance being forced. Go to Step (f);
   d) if the new state is PF and previous state Diagnosis, $t_{\text{next}} = t_{\text{rem}} + t_s$, the expected failure state before the transition to Diagnosis is made y_{next}, and y_m is set to Diagnosis. Go to Step (f);
   e) if the new state is Idle, $t_{\text{next}} = \infty$. y_m is set to PM if the node is from PM, and CM if it is from Diagnosis. Go to Step (f);
   f) steps (d) and (e) involve maintenance suspensions. For these and the case involving PM suspension in Step (c), the time, t_{spare}, the spares will be delayed by is sampled from the appropriate distribution. Update $\boldsymbol{\tau}_{\text{spare}}$, such that $(i, \boldsymbol{\tau}_{\text{spare}}) = t_{\text{spare}} + t_s$;
   g) update the node's state history, the flow property vectors, and $\boldsymbol{\tau}$, such that $(i, \boldsymbol{\tau}) = t_{\text{next}}$.
7) Identify nodes for which spares have been made available, that is, $(i, \boldsymbol{\tau}_{\text{spare}}) = t_s$. For each node, i, update $\boldsymbol{\tau}_{\text{spare}}$, such that $(i, \boldsymbol{\tau}_{\text{spare}}) = \infty$, h_1 if y_m is CM or Diagnosis, and h_2 otherwise.
8) Compute h_{1f} and h_{2f} and call Algorithm 3 (see Fig. 7).
9) If the current and previous flow property vectors differ:
   a) restart nodes in shutdown, compute system flow, and shutdown nodes, as proposed in [22];
   b) for each output node, update its performance history if its current and previous performances differ.
10) Save the current node flow property vectors.
11) Compute $h_{1f} = h1 \cap \Omega \cap \eta_1$ and $h_{2f} = h2 \cap \Omega \cap \eta_2$ and call Algorithm 3 for the second time. This step

accounts for those components maintainable only while in Shutdown.

12) Set the next simulation time, $t_s = \min(\min(\boldsymbol{\tau}), \min(\boldsymbol{\tau}_{\text{spare}}))$.

13) Repeat Steps 6–12 until $t_s > T_m$, updating $\boldsymbol{\tau}$, the flow property vectors, node state histories, and output performance histories at every transition.

14) Repeat Steps 2–13, Nsamples times, saving the final node histories at every trial.

15) Determine the system performance indices.

The desired performance indices are $(\text{EENS})_{\text{eff}}$, $\{N_i^{\{\text{cm}\}}, N_i^{\{\text{pm}\}}\}_{M\times 2}$, $\{t_i^{\{\text{cm}\}}, t_i^{\{\text{pm}\}}\}_{M\times 2}$, and $\{s_i^{\{\text{cm}\}}, s_i^{\{\text{pm}\}}\}_{M\times 2}$. The latter is yielded directly by the simulation algorithm, $(\text{EENS})_{\text{eff}}$ is computed from the performance histories of output nodes, and the remainder from the state transition histories of components. $t_i^{\{\text{pm}\}}$ is given by the average time spent by component i in the PM state (e.g., state 5 in Figs. 2 and 3), $t_i^{\{\text{cm}\}}$ is given by the average time spent in Diagnosis and CM (e.g., states 7 and 3 in Figs. 2 and 3, and states 3, 5, 7, and 9 in Fig. 4), $N_i^{\{\text{cm}\}}$ is given by the average number of transitions from all CM states to the Working state (e.g., transition 3-1 in Figs. 2 and 3, and transitions 3-1 and 5-1 in Fig. 4), and $N_i^{\{\text{pm}\}}$ is given by the average number of transitions from the PM state to the Working state (e.g., transition 5-1 in Figs. 2 and 3). These indices are substituted in the equations proposed in Section II-B to compute the system loss function.

The simulation procedure, with its associated algorithms, accounts for most of the forced and conditional transitions. As a result, an appreciable number of these transitions could be omitted from the component model with no adverse effects on the simulation outcome. For instance, the Shutdown state and its related transitions could be omitted altogether. This, however, does not mean shutdown and restart are not accounted for during simulation. Of the remaining forced and conditional transitions, only those to and from the Diagnosis state, from PM to Idle state, and from PM to APM state (if applicable) are required; the rest could be omitted. Applying this new information to the component models presented in Figs. 2 to 4, for instance, would result in much simpler models.

IV. Case Studies

The proposed framework is implemented in the open-source MATLAB-based toolbox, OpenCOSSAN [30], [31], and used to identify the optimal maintenance strategies for two power systems.

A. *Case Study 1: A 50-MW Hydroelectric Power Plant*

In this case study, a two-unit hydroelectric power plant is analyzed. It is a slightly modified model of the Bumbuna hydroelectric power plant, a 50-MW plant in Sierra Leone. Its two units are similar, and each, rated 25 MW, consists a butterfly valve, a turbine, a generator, and a circuit breaker. Their generated power is synchronized in the synchronizing unit and fed to the step-up transformers for onward transmission. These transformers are also rated 25 MW, and when one is

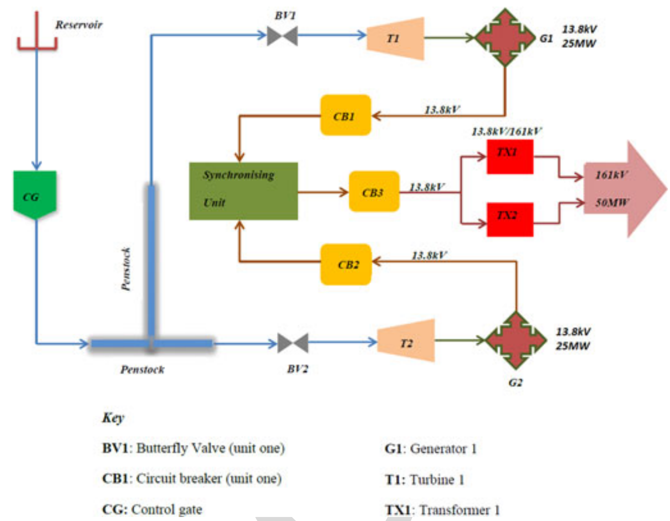


Fig. 8. Schematic of a two-unit hydroelectric power plant.

unavailable, the plant is reconfigured such that only one unit operates. The plant's schematic representation is shown in Fig. 8, and its reliability data are shown in Table III. All failure and repair times are in hours, and costs are in British Pounds (£). The unit cost of electricity is £ 0.5, the fixed wage per maintenance team is £ 7 per hour, and a negligible cost is per maintenance call. It is worthwhile noting that the data presented in Table III are assumed and are, therefore, for illustrative purposes only. Ideally, such data are based on actual field data extracted from component maintenance history.

1) Modeling the Plant and Its Components: The following assumptions are considered.

1) All components operate at only two distinct performance levels.
2) Components are ranked for maintenance in their order of arrival in the maintenance queue.
3) There is only one maintenance group.
4) The load on the plant is fixed at 50 MW, and there is sufficient water in the reservoir to meet this demand.
5) The failure rates of the control gate and penstock are negligible.

Fig. 9 shows the network model of the plant. The components of unit 1, i.e., valve-1, turbine 1, generator-1, and breaker-1, are, respectively, represented by nodes 1–4, and their counterpart in unit 2 are represented by nodes 5–8. Nodes 9–14, respectively, represent the synchronizer, breaker-3, transformer-1, transformer-2, dam, and the external load. Assuming perfect links between components, the parameters of the network are obtained as proposed in [22]. For this system, the number of nodes, M', is 14, while the number of maintainable components, M, is 12. The state-space diagrams of the components, without maintenance delays, are shown in Fig. 10. Under the range of possible maintenance regimes proposed in Section II-C, these state-space diagrams can be transformed into those in Figs. 2 and 3. Since the demand and source (dam) capacity are fixed at 50 MW, nodes 13 and 14 have a single state of capacity 50 units.

TABLE III
COMPONENT AND SYSTEM DATA FOR THE HYDROELECTRIC POWER PLANT

Component	Valves	Turbines	Gens.	Breakers	Synch.	Xfmr.
Failure time distribution	Wb(1000, 1.5)	Wb(4125, 2.1)	Wb(2000, 2)	Exp(3750)	Exp(3250)	Exp(2500)
Repair time distribution	Exp(40)	LogN(106, 5)	Exp(150)	Exp(36)	Exp(96)	Exp(80)
PM interval	U(500, 625)	U(1125, 1250)	U(1125, 1250)	U(2125, 2175)	U(2125, 2175)	U(2125, 2175)
PM duration	Exp(8)	Exp(21.2)	Exp(30)	Exp(7.2)	Exp(19.2)	Exp(16)
Diagnosis duration	Exp(5)	Exp(14)	Gu(20, 3.24)	G(5, 2)	Exp(16)	LogN(16, 2)
Spares cost(CM)	1624	2100	1944	1006	2245	2700
Spares cost(PM)	1055.6	1365	1263.6	653.9	1459.25	1755
PM cost/hr	162.5	243.75	203.13	101.56	243.75	264.06
CM cost/hr	250	375	312.5	156.25	375	406.25
Spares delay			Exp (24)			
Probability of Component Replacement During Maintenance						
CM (p_i)	0.5	0.55	0.8	0.9	0.7	0.6
PM (q_i)	0.8	0.9	0.96	0.42	0.4	0.45
Mean Fraction of PM Duration Before Component Replacement Becomes Eminent						
Fraction (k_i)	0.25	0.25	0.25	0.25	0.25	0.25

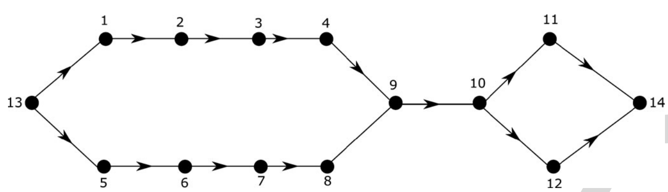
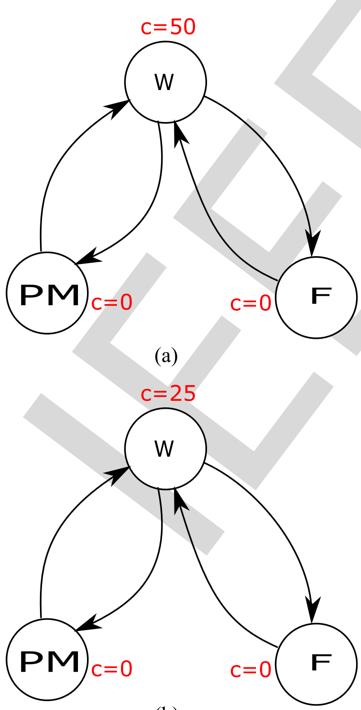


Fig. 9. Plant's network model.



(a)

(b)

Fig. 10. State-space diagrams of components. (a) Nodes 9 and 10. (b) Other nodes but 13 and 14.

The reconfiguration procedure used in the simulation shuts down nodes when their load flow drops below a threshold. To enable plant reconfiguration when only one transformer is available, a minimum load restriction is imposed on the turbines. The choice of the turbines, however, is arbitrary, as any of the unit nodes would do, due to their being connected in series. With only node 11 or 12 available, the load flow from node 13 drops to 25 MW, which is divided equally between the two units if they both are in operation. The threshold flow for each turbine, therefore, is set to a value slightly greater than 12.5 units (say 12.52), and 0 for all the other nodes.

2) Effects of Maintenance on System Performance and Reliability: The plant is analyzed separately under the assumptions that its components are nonrepairable, subject to PM only, CM only, and both maintenance types. With the exception of the nonrepairable case, there is no restriction on the number of parallel maintenance actions that can take place. The maintenance team size in each case, therefore, is expressed as (0 0), (0 12), (12 0), and (12 0), respectively. Dedicated maintenance is used in the second and third cases to ensure that only the intended maintenance type is carried out (e.g., no CM during a PM only policy). This stage of the optimization is aimed at investigating the relative effects of the various maintenance strategies on the plant's reliability, performance, and loss function. It identifies the candidates for the optimal maintenance strategy and determines whether or not to proceed with the search for the optimal maintenance team size. This prevents searching in unlikely regions or strategies, thereby reducing the computational cost.

Figs. 11 and 12, respectively, show the reliability and instantaneous performance of the plant as a fraction of its nominal output, for a mission time of 10^4 hours and 5×10^3 Monte Carlo samples. Plant reliability is defined with respect to complete outages, however, excluding those due to PM (scheduled outages). The objective is to study the survivability of the plant, which scheduled outages would underestimate. For instance,

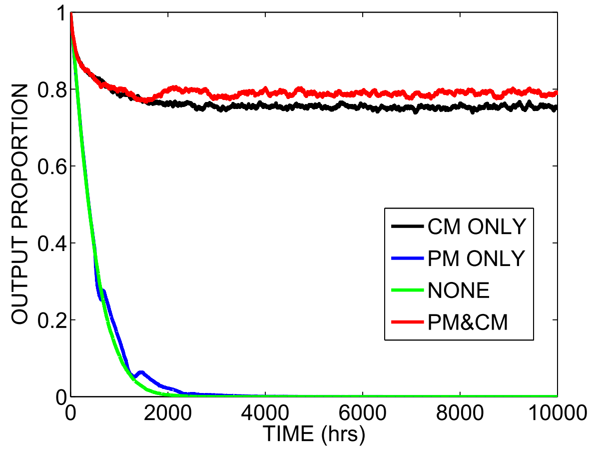


Fig. 11. Plant output performance.

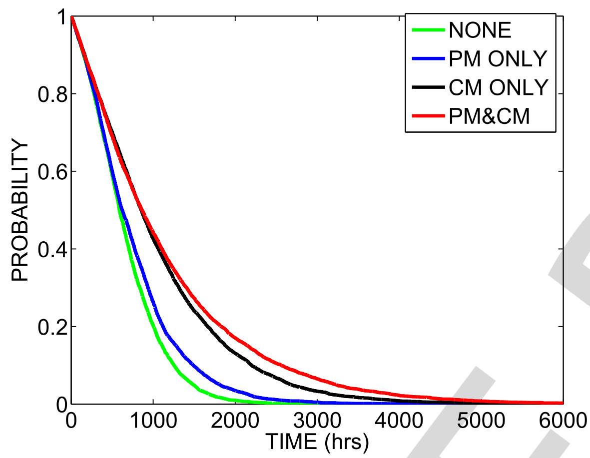


Fig. 12. Plant reliability.

more frequent outages may be experienced under a maintenance strategy incorporating both PM and CM than one with CM only. In practice, scheduled outages do not count toward a systems's survivability, since they are out of choice rather than failure, hence the need for their disregard in its survivability analysis. In summary, plant reliability at time t is the nonoccurrence probability of complete-outage-inducing failures in the interval $[0, t]$.

The reliabilities and instantaneous performances defined by Figs. 11 and 12 depict the upper bounds for the various maintenance strategies. As expected, both types of maintenance (PM and CM) action indeed improve the reliability and performance of the plant. The impact of PM, however, is only slight, given that 50% of the components exhibit an exponential failure characteristic. For such components, PM only reduces their availability without an improvement in reliability [23]. PM, therefore, is the most effective in systems with ageing components. Table IV presents the upper bound of the expected plant output and the corresponding loss for each maintenance strategy. The notation $[a, b]$ denotes a strategy made up of a combination of regimes a and b, as described in Section II-C. A review of the trend

TABLE IV
PLANT EXPECTED OUTPUT AND LOSS

Strategy		Output (GWh)	L (£10^6)
None		23.6646	238.17
PM only		26.0639	237.82
CM only		382.2114	60.98
PM+CM	[1,4]	370.9891	66.38
	[1,5]	384.2075	59.91
	[2,4]	369.1798	67.51
	[2,5]	383.5723	61.42
	[3,4]	396.2899	53.63
	[3,5]	388.2218	58.07

TABLE V
OPTIMAL PLANT LOSS AS A FUNCTION OF MAINTENANCE STRATEGY

Strategy	L (£10^6)	Number of teams
[1,4]	65.6617	2
[1,5]	59.2353	2
[2,4]	66.8779	3
[2,5]	59.6466	3
[3,4]	52.8917	5
[3,5]	57.3184	4
CM only	60.1399	4

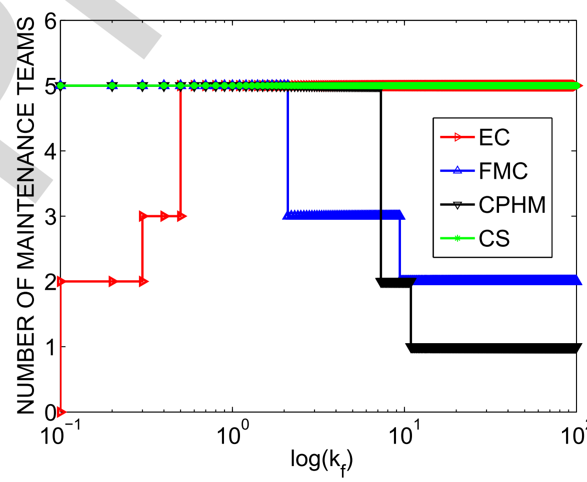


Fig. 13. Optimal maintenance team size sensitivity to costs.

portrayed in Figs. 11, 12, and Table IV suggests that a maintenance strategy incorporating both PM and CM is desirable. The losses in Table IV are yielded by the maximum number of maintenance teams; the optimal loss in each case, therefore, will be provided by fewer maintenance teams. These teams are determined by the procedure proposed in Section II-D.

3) Optimal Maintenance Strategy Identification: It is clear that the nonrepairable and "PM only" strategies are very inefficient. The plant, therefore, is analyzed for the other strategies, using the same mission time and the number of samples as in the preceding section. The optimal solution for each strategy is identified and recorded, as shown in Table V.

From these, the best maintenance strategy and the optimal number of maintenance teams are deduced as [3,4] and 5,

TABLE VI
OPTIMAL MAINTENANCE STRATEGY SENSITIVITY TO COSTS

	Cost Element			
	EC	FMC	CPHM	CS
Strategy	(0 0), $k_f = 0$ $[3,4]$ $k_f > 0$	$[3,4]$ $\forall k_f$	$[3,4], 0 \leq k_f < 70.9$ $[3,5],$ $k_f \geq 70.9$	$[3,4]$ $\forall k_f$

respectively. To explore the existence of a more optimal solution for this strategy, the plant is reanalyzed under dedicated maintenance. It is observed that for the same number of teams, shared maintenance strategies produce a better plant performance.

The optimal strategy being [3,4] is in agreement with the preliminary results presented in Table IV. Therefore, the optimal solution would have been obtained using this strategy alone. However, the other strategies were considered to establish a relationship between the optimal maintenance team size and maintenance strategy.

4) Sensitivity to Cost Levels: The robustness of the optimal maintenance strategy to variations in cost of electricity (EC), fixed cost per maintenance team (FMC), fixed cost per hour of maintenance (CPHM), and cost of spares (CS) is investigated. Fig. 13 shows how the number of maintenance teams required for optimal performance varies with $k_f \mid 0 \leq k_f \leq 100$, where k_f is the ratio of new cost to the original cost provided in Table III. It is evident from the figure that the optimal maintenance team size is insensitive to the cost of spares but exhibits a fair degree of sensitivity to the other costs. In contrast, the optimal maintenance strategy is insensitive to all four cost elements up to $k_f = 70.9$ (for CPHM), beyond which [3,5] becomes the optimal strategy, as shown in Table VI.

In practice, when inflation occurs, it affects all the cost elements concurrently. The sensitivity of the optimal solution in such a scenario is investigated. It is observed that with $k_f = 0$, the maintenance strategies are all equivalent, since all the services are basically provided free-of-charge. Beyond this value, the optimal maintenance strategy and the number of teams remain constant at [3,4] and 5, respectively, for the entire range of k_f. The optimal loss, however, increases according to Fig. 14. This strange behavior is explained by the dominance of the cost of electricity in the loss equation (see Section II-B). When all the four costs change by the same factor, the resultant effect is dominated by the electricity cost, for $k_f > 0.4$, and the other costs otherwise.

A comparison of the trends portrayed in Figs. 13 and 15 supports this theory. Fig. 15 is obtained by holding fixed the cost of electricity and varying the maintenance costs. Expectedly, it shows a decrease in the optimal maintenance team size, with rising maintenance costs. Indeed, with high maintenance costs, the only logical decision is downsizing the maintenance team to ensure sustainability.

5) Computational Costs: The simulations were run on a *48-core, 1895.257-MHz AMD Opteron(tm) 6168 processor* using 19 cores running in parallel. Less than 1 min was required for the nonrepairable system and an average of 8.95 min per candidate solution was required for the system under PM and CM.

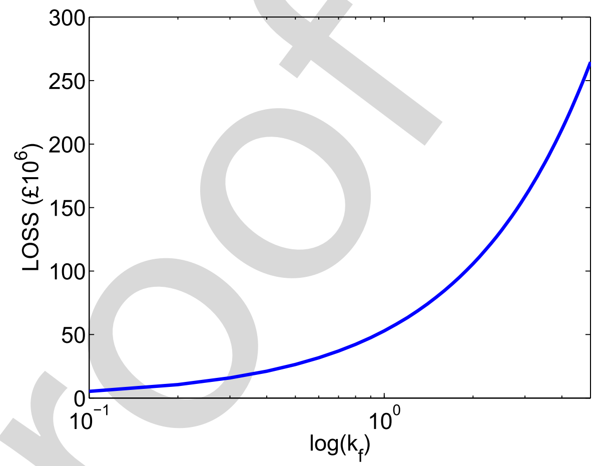


Fig. 14. Optimal system loss sensitivity to cost-level variation.

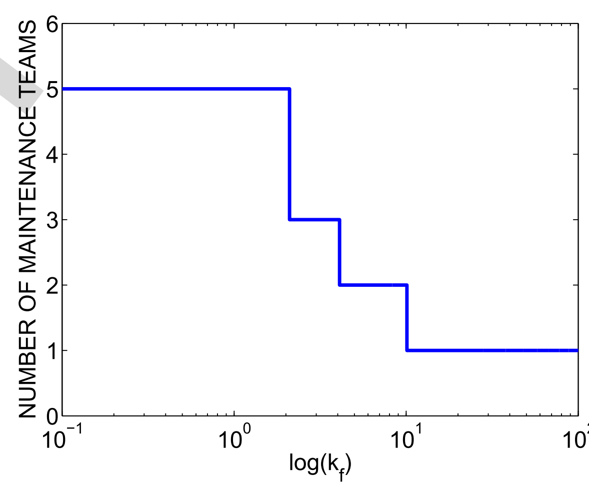


Fig. 15. Sensitivity of optimal solution to concurrent variation in FMC and CPHM.

6) Discussions: Analytical approaches do not make a feasible option for the analysis of complex systems with realistic attributes. Simulation algorithms, on the other hand, are disadvantaged by their large computational costs, made worse when employed in optimization procedures. This, often, is attributed to the large number of samples required for a dependable estimate of the system performance indices. Therefore, the tradeoff between accuracy and moderate computational burden is worth adequate attention. Another limiting constraint of great importance is the mission time, which should be selected such that the performance indices obtained reflect the true long-term indices of the system. This requires that the mission time be sufficiently greater than the time the system takes to attain the steady state. In the presented case study, 5000 samples are just enough to provide an acceptable degree of accuracy and a manageable computational burden. Also, as deduced from Fig. 11, the plant's steady-state attainment time is about a fifth of its mission time. These attributes endorse the dependability of the optimization outcome.

The analyses suggest that the optimal number of maintenance teams is maintenance strategy dependent. They also reveal that returning components into operation during maintenance suspensions improves system performance. This improvement is attributable to the increased availability of the components culminating in a lower EENS. The exception is the case when PM is initiated only while components are not in operation. In this regime, the initiation of a component's PM is determined by the failure characteristics of other components. Therefore, when the component is returned into operation, its PM resumes only on the occurrence of another shutdown event. The likelihood that the component fails in this interval is higher than in the other regimes due to the longer wait times. The result is: a fewer PM actions, more failures, longer component downtimes, and a higher EENS. These consequences are minimized by keeping the component out of operation until PM resumes. However, in both cases, initiating PM only while components are not in operation yields the best performance.

The range of k_f used in the sensitivity analysis is a little unrealistic for practical applications. The range of interest, therefore, is conservatively chosen to be $0 \leq k_f \leq 2$, depicting an inflation of -100% to $+100\%$. In this range, the optimal maintenance strategy is unaffected by variations in cost levels, though the number of teams required for optimal performance varies with the cost of electricity. The following, therefore, is recommended for the hydroelectric power plant.

1) PM should be carried out only when a component is not in operation, that is, it should coincide with a shutdown event that renders the component inactive.
2) Components should be kept out of operation during maintenance interruptions.
3) At the current cost levels, five maintenance teams, in a shared maintenance strategy, are required for optimal performance. However, this should be scaled down to 3, 2, 1, and 0 when the cost of electricity deflates by 50%, 60%, 90%, and 100%, respectively (see Fig. 13).
4) As evidenced in Figs. 11 and 12, PM does not quite improve the overall performance of the system, contrary to anticipations. This, as explained earlier, could be due to subjecting components exhibiting exponential failure characteristics to needless PM. It is anticipated that if PM is not carried out on these components, additional gains could be made from improved plant availability and reduced maintenance costs. This hypothesis is tested and, as expected, results in an output gain of 1.82% and a corresponding system loss reduction by 7%. PM, therefore, should not be carried out on the breakers, synchronizer, and transformers.

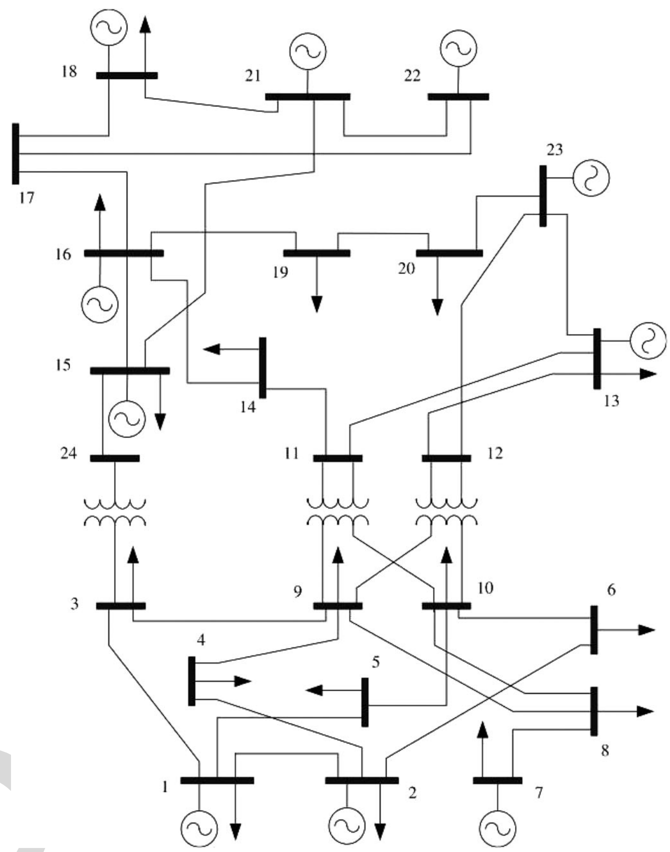


Fig. 16. Single-line diagram of the IEEE-24 bus Reliability Test System.

B. Case Study 2: The IEEE-24 Bus Reliability Test System

In this case study, we consider a more realistic system in order to showcase the applicability of the proposed approach to systems of practical nature. Shown in Fig. 16 is the single-line diagram of the IEEE-24 bus one-area test system, adapted from [32]. It is composed of 24 buses, 34 power lines, ten generation stations, and 17 load points. Its total generating capacity is 3405 MW and a varying load which annual peak is 2850 MW. The total generating capacity and load are distributed across the network as described in [33]. The buses are assumed perfectly reliable and the transmission lines, binary state. We retain the failure and repair characteristics of the transmission lines but modify a few other properties to make the system more realistic and compatible with the proposed approach. These modifications are thus summarized as follows.

1) Multiple generation units at a bus have been represented by a single unit with a generating capacity equivalent to the sum of the generating capacities of the units.
2) To make the network more sensitive to the unavailability of transmission lines and generation units, the maximum transmission capacities of the former and minimum allowable loads of the latter are considered in the analysis. These capacities and limits are given in [33] and [32], respectively. Note that the minimum load for the unit at bus 22 is set to 25 MW instead of 300 MW suggested

TABLE VII
MAINTENANCE DATA FOR GENERATION UNITS

Gen. Type	Bus Number	Spare Usage Prob.		PM		Transition Distribution Parameters				
		CM	PM	Interval	Duration	1-2	2-1	2-3	1-3	3-1
1	22	0.7	0.9	1200	U(156,180)				Wb(2234,2)	Exp(20)
2	1 & 2	0.9,0.25	0.9	1200	U(60,66)	Exp(980)	Exp(20)	Wb(1106,2.3)	Wb(2212,2)	Exp(40)
3	7	0.8,0.4	0.9	1200	U(60,66)	Exp(600)	Exp(25)	Wb(677,2.3)	Wb(1354,2)	Exp(50)
4	15,16 & 23	0.8,0.3	0.9	1000	U(81,87)	Exp(480)	Exp(20)	Wb(542,2.3)	Wb(1083,2)	Exp(40)
5	13	1.0,0.5	0.9	1000	U(102,108)	Exp(575)	Exp(50)	Wb(649,2.3)	Wb(1298,2)	Exp(100)
6	18 & 21	1,0.6	0.9	1000	U(123,129)	Exp(550)	Exp(75)	Wb(621,2.3)	Wb(1241,2)	Exp(150)

in [32]. The reason for this is that its contribution to the total load when every component works correctly is only about 37.5 MW. A minimum allowable load of 300 MW, therefore, would mean that it operates only on failure of another unit. This, in other words, reduces the unit to cold standby, thereby defeating our intention of making every component useful to the system throughout the mission.

3) The buses are assigned maximum capacities according to the following rules.
   a) For load and generation buses, the maximum capacity is arbitrarily set to three times the capacity of the generation unit or load.
   b) For buses with both a generation unit and load, the capacity is set to three times the generating capacity or load, whichever is greater.
   c) For all other buses, the capacity is set to three times the maximum of the capacities of the buses they are connected to.
4) Each generation unit, with the exception of the unit at bus 22, is assumed to exist at three possible distinct output levels: 100%, 50%, and 0% of its rated capacity. Unit 22 operates at only two levels: 100% and 0% rated capacity.

1) Maintenance Information: The failure times of the transmission lines are exponentially distributed. As a consequence, they undergo CM only, with an assumed 0.9 likelihood of spares being used. Due to their less bulkiness, it is assumed that the maintenance crew are able to carry with them these spares. The maintenance of the lines, therefore, is immune to delays in the availability of spares.

The generation units, on the other hand, undergo both PM and CM and are susceptible to all the operational dynamics described in Section II. Table VII contains their failure and maintenance parameters, where states 1–3, respectively, represent nominal performance, partial, and complete failure. Their replacement probability during CM is represented by a pair, which elements, respectively, define the probabilities associated with states 3 and 2. Where applicable, the diagnosis and CM durations have the same distribution, with means in the ratio 1:4. For instance, the transition of the unit at bus 13 from state 3 to 1, denoting repairs from complete failure, is exponentially distributed with mean 100. Therefore, the diagnosis and CM durations are also exponentially distributed with means 20 and 80, respectively. All transition times are in hours, and k_i for generation units is conservatively assumed to be 0.3. Also note that the data presented in Table VII are for illustrative purposes only.

TABLE VIII
MAINTENANCE COSTS FOR GENERATION UNITS

Gen. Type	CM		PM	
	CS	CPHM	CS	CPHM
1	180	20	108	12
2	180	20	108	12
3	180	20	108	12
4	200	25	120	15
5	280	40	168	24
6	300	50	180	30

2) Maintenance Grouping and Costs: The network components are arranged into three maintenance groups, and each group is maintained by a separate maintenance company. The transmission lines above buses 11, 12, and 24 make maintenance group 1, the remaining lines make group 2, and the generation units constitute group 3. Each maintenance team in groups 1 and 2 is paid a fixed $\pounds 5$ per hour and a fixed $\pounds 100$ per successful maintenance action. Teams in group 3 earn $\pounds 8$ every hour and $\pounds 120$ for every successful maintenance action. Due to economic constraints, the operator imposes the total number of maintenance teams to not exceed 16. The cost of one transmission line spare is averaged at $\pounds 150$, the cost per hour of transmission line maintenance, at $\pounds 15$, and the cost levels for the generation units, as defined in Table VIII.

3) Objective: The current maintenance strategy, hereafter referred to as the base strategy, assumes that CM of partially failed components and PM can be initiated at any time, subject to the availability of maintenance teams. For one annual load cycle of 8736 h (see [33]) and $\pounds 100$ per MWh of electricity consumed, we determine the optimal maintenance team size for this strategy and compare its effectiveness with three complex strategies. The base strategy, for simplicity, is labeled strategy 1, and the complex strategies, as outlined, are thus outlined as follows.

1) Strategy 2: PM and CM of partially failed generation units only when they are not required.
2) Strategy 3: PM and CM of partially failed generation units only when system performance is nominal.
3) Strategy 4: PM of generation units only when system performance is nominal, but CM of partially failed units can be carried out at any time.

Each maintenance strategy is computed for the case when the units:

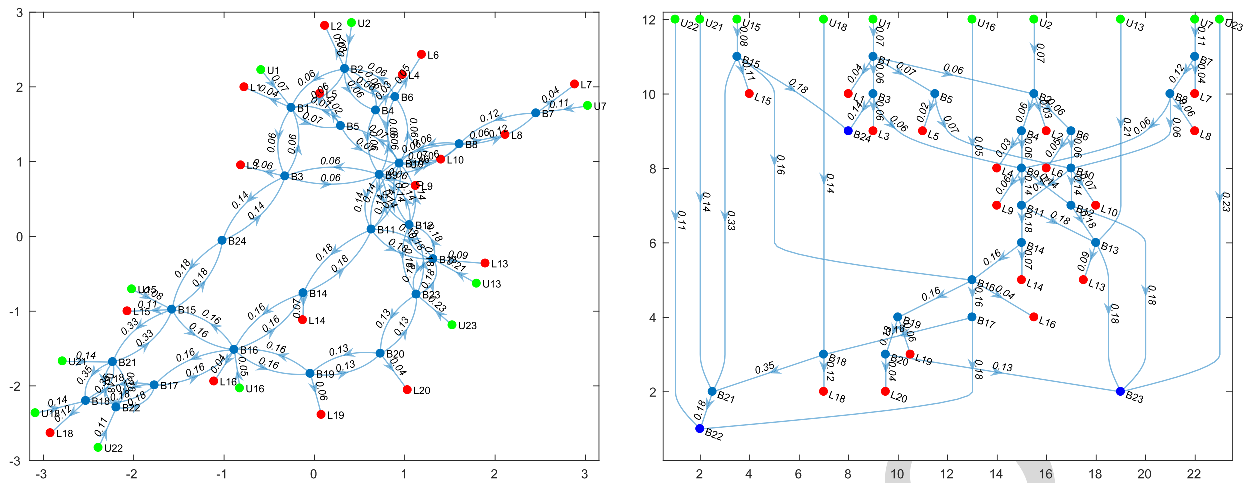


Fig. 17. System graph model. (a) Both reciprocal edges shown. (b) Only one reciprocal edge shown.

a) are kept out of operation during maintenance suspensions;
b) are returned into operation during maintenance suspensions.

4) System Modeling: Since the goal is to identify the optimal maintenance strategy, a dc flow analysis, using the procedure proposed in [22], is employed to compute the system reliability and performance indices. The buses, generation units, and load points are modeled as nodes, while the transmission lines are modeled as edges in the system graph model. In this case study, we have retained the edge attribute of the transmission lines to keep the number of nodes moderate and improve performance. Consequently, the vector of maximum edge capacities is modified after every transition involving a transmission line, and both this vector and the vector of node capacities are required for system flow calculation. Fig. 17(a) shows the graph model of the system, where Un and Ln, respectively, denote the generation unit and load point at bus n. Fig. 17(b) shows the same graph but with only one edge of each reciprocal pair [22] shown for clarity. In both cases, the number along each edge defines the maximum flow along that edge as a fraction of the annual peak load.

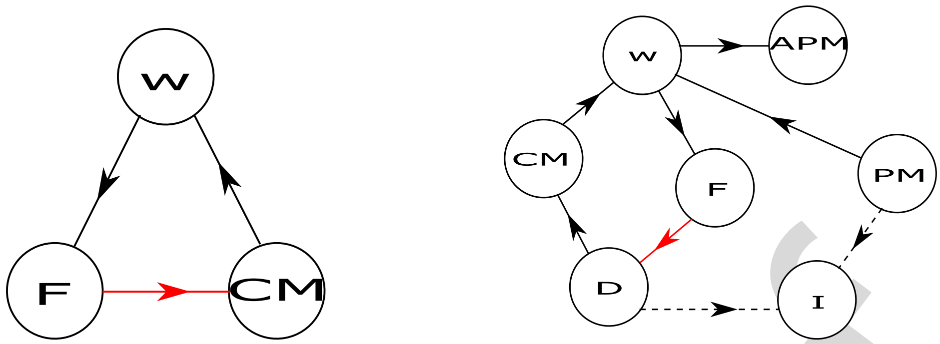
The effective EENS of the system (given the multiple load points) could be computed as proposed in Section II. However, the computation is rendered less complicated by representing the global system output by a virtual node, which flow is the sum of the flows through all 17 load points. The flow history of this virtual node is recorded during simulation and subsequently used to compute the effective EENS, instead of all 17 nodes. Being mindful of the computational demand of simulation algorithms, we employ a smart procedure to treat the variable demand on the system. Recall that the objective of system reliability analysis is to determine the maximum achievable system performance as a consequence of component failure and maintenance. For this reason, we obtain the instantaneous system performance, $Y(t)$, assuming that the demand is fixed at its peak annual value. However, under this assumption, the system is no longer strictly demand driven (since the actual demand varies with time), and $Y(t)$ has to be normalized to make it compatible with (1) and (2). The normalization entails expressing $Y(t)$ as a function of the same time step as the instantaneous demand, $Y_d(t)$, such that they both have equal lengths, and applying the following:

$$Y(t) = \min\{Y(t), Y_d(t)\}. \tag{17}$$

Normally, variable demand is treated by performing the simulation with respect to the time step defined by the demand and the events generated by component failures and maintenance. It is, therefore, easy to deduce the computational efficiency of the procedure employed here, relative to the widely practiced. The procedure is correct for all single-load-point systems, as well as multiple-load-point systems, where the quantity of interest is the total output, and not the output through the individual load points.

To derive the set, $\mathbb{N}$, of possible maintenance team combinations, we ignore the possibility of a 0 maintenance team in any of the maintenance groups. This is due to the fact that we already know (from the previous case study) nonrepairable maintenance strategies to be grossly inefficient. Recall also that maintenance groups 1 and 2 are composed of equal number of components with the same failure and repair characteristics. They, therefore, have the same optimal maintenance team size. Given these constraints and the upper bound imposed by the operator on the total number of maintenance teams, $\mathbb{N}$ contains 50 maintenance team combinations.

5) Component Modeling: Figs. 18 and 19 are the system's simplified component models, showing only the required transitions, as discussed in Section III-E. Since the transmission lines are not susceptible to maintenance interruptions, their failure diagnosis and actual repair have been collectively represented by the CM state. This, however, implies that the number of spares used cannot be directly obtained from the simulation, as spares used are accounted for only if the component enters Diagnosis or PM state (see Algorithm 2). The total spares used, therefore, are obtained from the product of the spares usage probability and the number of CM to W transitions. Note that the models in Figs. 18 and 19 are based on the assumption that components



(a) (b)

Fig. 18. Simplified multistate model for binary-state components. (a) Transmission lines. (b) Generation unit at bus 22.

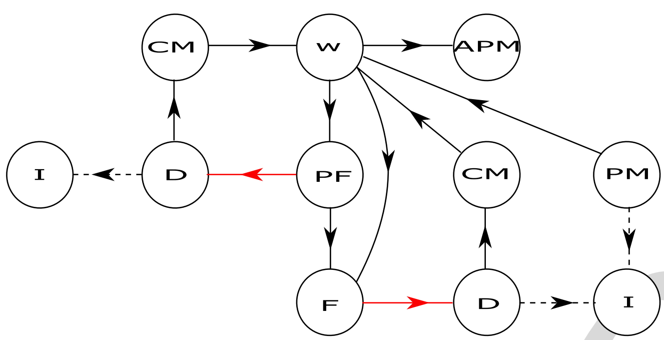


Fig. 19. Simplified multistate model for multistate generation units.

TABLE IX
OPTIMAL SYSTEM LOSS AS A FUNCTION OF MAINTENANCE STRATEGY

Strategy		EENS(%)	L$\left(£10^6\right)$	Optimal number of teams		
				Group 1	Group 2	Group 3
1	a	0.3940	6.6324	1	1	3
	b	0.2468	4.4712	2	2	3
2	a	2.4218	37.6617	1	1	4
	b	2.4780	38.6764	3	3	4
3	a	1.3592	21.3563	1	1	3
	b	1.5049	23.6498	1	1	4
4	a	0.3373	5.9026	1	1	5
	b	0.2128	3.9513	2	2	3

are kept out of operation during maintenance suspensions. Those for the case when components are returned into operation can be easily deduced from Figs. 2–4. It is also worthwhile noting that the simplified component models for regimes 1–3 of Section II-C are equivalent.

6) Results and Discussions: The system was analyzed on the same computer used for the previous case study, and the outcome is summarized in Table IX. The table provides the EENS as a percentage of the total expected output, the expected loss, and the optimal maintenance team combination for each strategy. Each sample of a candidate solution took an average of 0.8 s, using ten MATLAB workers. Given the large number of candidate solutions, the number of samples per candidate solution was set to 500. The sensitivity of the optimal solution to the costs considered in the previous case study and a few other costs was also investigated. The additional costs considered are as follows.

1) Cost per hour of CM and cost per CM call (CPHM1).
2) Cost per hour of PM and cost per PM call (CPHM2).
3) Total maintenance cost (MC), a combination of FMC, CPHM1, CPHM2, and the cost per CM and PM call.
4) All costs relevant to the system loss function (ALL).

Deducing from the data in Table IX, the optimal maintenance strategy is strategy 4(b). In this strategy, CM of partially failed generation units can be initiated at any time, but PM, only when system performance is nominal, with components returned into operation during maintenance suspensions (see the beginning of this subsection). Postponing both CM and PM until component shutdown (strategy 2) appears to be the most inefficient, contrary to what obtained in the previous case study. This observation reiterates the point that the optimality of a given maintenance strategy depends on specific properties of the system. For $0 \leq k_f \leq 100$, strategy 4(b) remains optimal, but the optimal number of maintenance teams varies, as depicted in Fig. 20. It should be noted that cost parameters with no effect on the optimal number of maintenance teams have been left out in Fig. 20(a) and (b). Given that maintenance groups 1 and 2 are made up of the transmission lines only (which do not undergo PM), CPHM and CPHM1 are equivalent, explaining the absence of CPHM1 and CPHM2 in Fig. 20(a). A notable conclusion drawn from Fig. 20 is that the optimal number of maintenance teams is mostly affected by the cost of electricity (EC) and the fixed cost per maintenance team (FMC). It is also easily deducible that the number of teams required for optimality reduces and increases with reduction in EC and FMC, respectively, both observations conforming to common reasoning.

Fig. 21 shows the variation in system loss with changes in cost levels in the range $0 \leq k_f \leq 2$. For clarity, system response over the ranges $0 \leq k_f \leq 1$ and $1 \leq k_f \leq 2$ has been presented separately in Fig. 21(a) and (b), respectively. With $k_f = 1$ as reference, Fig. 21(a) defines the sensitivity of the total system loss to cost reductions and Fig. 21(b) to cost increments. In both cases, the cost of electricity and the overall maintenance cost impact system loss the most. However, the system shows very little sensitivity to both the cost of spares and the cost per hour of PM action, suggesting a few PM actions and low spares usage.

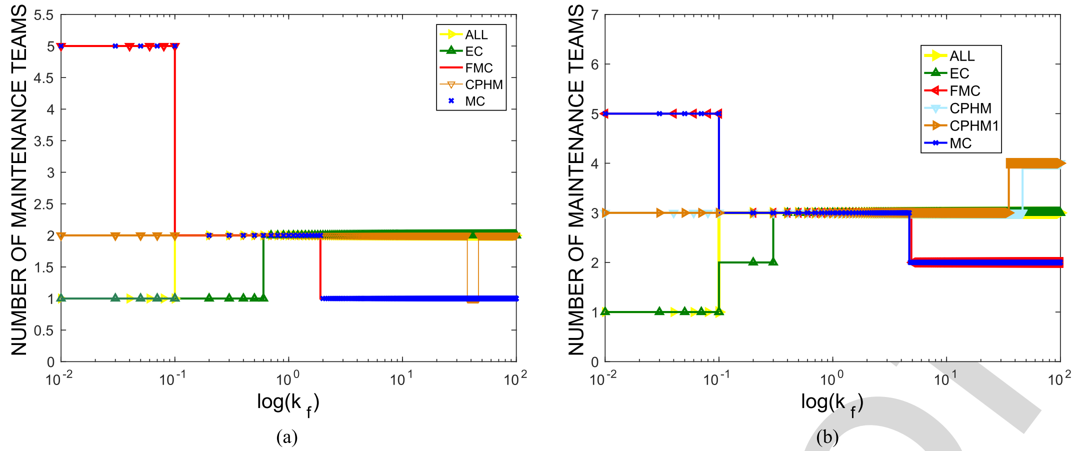


Fig. 20. Optimal maintenance team sensitivity to cost levels. (a) Groups 1 and 2. (b) Group 3.

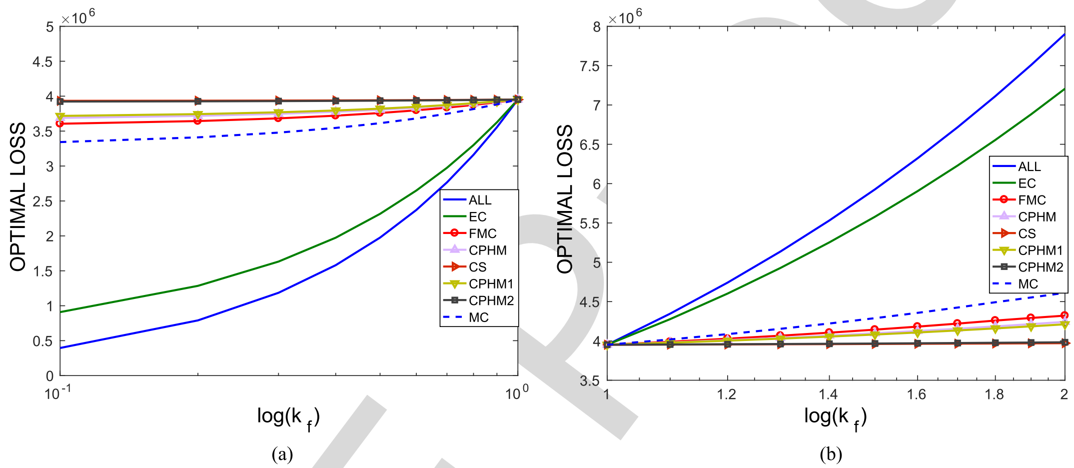


Fig. 21. System loss sensitivity to cost levels. (a) Cost reduction. (b) Cost increment.

The low system loss sensitivity to CPHM2 is explained by the fact that only ten of the 44 system components undergo PM. Given that strategy 4 imposes PM be initiated only if system performance is nominal, a good number of these components fail before their PM commences.

V. Conclusion

It is realistic to think that increasing the number of maintenance teams improves the performance and reliability of a multicomponent system. However, a threshold exists, exceeding which no gains are realized. Rather, it results in increased operational costs, borne from the imbalance between income and expenditure. This threshold, as expected, varies with the maintenance strategy, the input costs to the system's cost model, the topology of the system, and the nontopological functional relationships between its components.

In this work, a maintenance strategy optimization framework, aiding proper maintenance scheduling and robust maintenance decisions, has been presented. Applicable to both binary and multistate systems of any structure, the framework proposes a multistate model to define the behavior of components under various maintenance strategies. A nonsystem-specific event-driven Monte Carlo simulation based on the load-flow approach proposed in [22] is employed to replicate the operation of the system. This simulation algorithm, together with the multistate component model, enhances the implementation of complex maintenance strategies. For instance, a component may belong to two maintenance groups practicing dedicated and shared maintenance, respectively. There could also exist multiple maintenance groups with some initiating maintenance promptly and others only during a shutdown event or at the attainment of nominal system performance. Many more contrasting combinations of regimes are possible without the need to modify the simulation algorithm. The framework is also built on a cost model structured to allow the sensitivity analysis of the optimal solution from a single reliability evaluation. These attributes render it novel, efficient, and generally applicable to power and other systems alike.

The framework has been successfully used to optimize the maintenance strategies for two realistic power systems, obtaining insightful information on their maintenance. The relationship derived between the optimal number of maintenance teams and the cost of electricity, for instance, is a very useful tool, given a volatile electricity market. The framework, therefore, can shape the quality of maintenance-related decisions, even in the presence of external dynamics.

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