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Time-Based Preventive Maintenance without Time Shifts

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Abstract – **This paper presents a comprehensive approach to evaluating the time-based preventive maintenance (TbPM) strategy without time shifts by combining modelling and simulation of a generic single-component system using the class of Deterministic and Stochastic Petri Nets (DSPNs) with analytical approximation. The proposed model captures the dynamics among stochastic failures, corrective repairs, and deterministic preventive maintenance cycles, enabling steady-state availability assessment across both low- and high-availability systems. Using *TimeNET®*, simulation results are obtained for various combinations of Mean Time to Failure (MTTF), Mean Time to Repair (MTTR), Mean Time to Preventive Maintenance (MTPM), and Time to Preventive Maintenance (TTPM). Simulation results reveal distinct behavioural patterns: systems operating under TbPM generally exhibit slightly lower availability than those without preventive maintenance, particularly in high-availability regimes. However, in low-availability systems with short MTTF and properly aligned TTPM, TbPM can marginally enhance availability. The analysis also identifies a non-monotonic dependence of availability on TTPM, indicating the existence of an optimal maintenance interval that balances preventive and corrective actions, while reductions in MTTR yield the most substantial improvements in availability across all regimes. Closed-form expressions derived for approximate availability estimation closely match simulation outcomes, providing an efficient means for optimising maintenance scheduling in reliability-critical systems.**

Keywords – **Preventive Maintenance, System Availability, Deterministic and Stochastic Petri Nets (DSPNs), Modelling and Simulation, Analytical Approximation, High- and Low-Availability Systems**

I. INTRODUCTION

Preventive maintenance (PM) is founded on the well-known engineering principle that *"maintenance is not about fixing things that are broken, but about keeping things from breaking."* It represents one of the fundamental maintenance strategies aimed at maintaining assets in optimal operating condition through systematic inspection, service, and replacement activities performed at planned intervals. As a proactive approach, PM seeks to minimize unexpected breakdowns, reduce system degradation, extend the operational lifespan of equipment, and improve overall reliability and productivity, thereby contributing to cost efficiency and operational continuity. The essence of this philosophy is aptly conveyed by the classical aphorism of Desiderius Erasmus: *"Prevention is better than cure,"* emphasizing the importance of anticipating and preventing failures rather than reacting to them after they occur.

A widely used form of PM is time-based preventive maintenance (TbPM), where maintenance tasks occur at fixed, scheduled intervals. It is particularly effective for systems whose degradation can be statistically predicted. Depending on operational needs, TbPM may be performed while equipment remains active, thus maintaining availability, or during planned shutdowns that temporarily reduce availability but prevent more severe, unplanned failures.

In the domain of microwave systems, TbPM is critical due to the high sensitivity and precision required in their operation. Microwave communication and radar systems, satellite transceivers, and high-frequency measurement instruments all depend on the stable performance of components such as waveguides, amplifiers, oscillators, circulators, and antennas, which degrade over time from thermal stress, environmental exposure, and mechanical wear, causing signal drift, attenuation, or complete system failure if not maintained. Regular TbPM activities, including connector inspection, transceiver calibration, component replacement, and signal verification, preserve optimal performance, reduce uncertainty, and prevent downtime. Given the critical role of microwave systems in telecommunications, aerospace, defence, and industrial automation, even short periods of downtime can be costly, making structured and optimized TbPM indispensable for sustaining high availability and ensuring long-term reliability.

In the Industry 4.0 era, driven by Internet of Things (IoT), Artificial Intelligence (AI), advanced robotics, and cyber-physical systems, effective preventive maintenance has become a cornerstone of resilient and intelligent production systems. In such environments, integrating deterministic maintenance scheduling with stochastic representations of failure and repair dynamics is essential for capturing realistic system behaviour. This paper addresses precisely this challenge by proposing and evaluating a Deterministic and Stochastic Petri Net (DSPN) model of a time-based preventive maintenance strategy that operates on fixed time intervals without allowing time shifts, even when corrective maintenance (i.e., reactive repair) events occur. The proposed modelling framework provides a quantitative means of examining the interplay between scheduled TbPM activities and unplanned maintenance actions, thus enabling data-driven optimization of maintenance policies aimed at improving system availability, reliability, and overall performability in

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technologically complex environments. In addition, closed-form expressions are derived for approximate calculation of steady-state availability, providing computationally efficient and interpretable estimates of maintenance performance.

Accordingly, this study pursues three main objectives:

(1) To numerically validate system availability as a key performability metric through steady-state analysis of the proposed DSPN model using *TimeNET*®;

(2) To derive closed-form expressions for approximate steady-state availability, expressed as functions of MTTF, MTTR, MTPM, and TTPM, enabling fast and interpretable availability estimation;

(3) To demonstrate the practical applicability of both approaches in optimizing maintenance planning and improving the performability of systems operating under TbPM constraints, across low- and high-availability regimes.

Even though the developed framework is generic, it can serve as a valuable tool for both researchers and practitioners in the field of microwave engineering and related disciplines, supporting effective decision-making that can strengthen reliability, optimize maintenance scheduling, and sustain high availability of critical microwave systems.

The paper is organised as follows. Section II provides a concise overview of the research studies most closely related to the topic. Section III introduces the proposed simulation model, while Section IV presents the simulation results. The closed-form expressions for approximative availability evaluation are given in Section V. Section VI discusses the obtained results and outlines the main advantages and limitations of the proposed approach. Finally, Section VII concludes the paper and highlights directions for future research.

II. Related Research

Various classes of Petri Nets (PNs) have been widely used not only for system modelling and analysis, but also for addressing maintenance issues, availability, and reliability. They offer both a graphical system representation and a rigorous mathematical framework for conducting diverse analyses across numerous application domains. The following is a brief overview of recent related studies.

A Petri net (PN) approach to conduct availability analyses has been utilized for an offshore wind turbine with age-based (i.e., imperfect) preventive maintenance, along with Monte Carlo simulation [1], to model and study remote maintenance processes [2], and to assess the effects of railway maintenance on track availability [3]. A timed/stochastic Petri net-based maintenance model was used to consider degradation, inspection, repair processes, as well as random and aging-related failures of generic industrial equipment [4]. The class of hierarchical coloured Petri nets (HCPNs) was leveraged to model and optimise fleet spare inventory, cannibalization, and preventive maintenance [5] as well as to evaluate technological facilities' maintenance process in the context of the Industry 4.0 paradigm [6]. Stochastic coloured Petri nets (SCPNs) were used to model the maintenance process of a wheel- steering system, emphasising logistics and maintainability evaluation [7]. The class of stochastic and dynamic coloured Petri nets (SDCPNs) was used to formalize the predictive aircraft maintenance process [8] and to assess the safety and efficiency of aircraft maintenance strategies in conjunction with agent- based modelling and Monte Carlo simulation [9]. The class of generalised stochastic Petri nets (GSPNs) was used for planning and optimizing maintenance logistics of small hydroelectric power plants [10].

The work most closely related to this study is that of Hristoski and Dimovski (2023), who reviewed multiple maintenance strategies, including PM, and supported them with corresponding simulation models using the classes of Generalized Stochastic Petri Nets (GSPNs) and Deterministic and Stochastic Petri Nets (DSPNs), while aiming to establish solid frameworks for evaluating the effectiveness of various maintenance strategies [11]. Earlier, the same authors focused specifically on several TbPM strategies, including the model leveraged in this study, by developing DSPN-based modelling frameworks [12]. They also provided a numerical evaluation of a DSPN model regarding the availability of a single-component generic system, which is subject to failures, repairs, and TbPM cycles both with time shifts [13] and without time shifts [14].

This paper differs from (and extends) the previously mentioned studies in several ways, making it a novel contribution:

(1) *Focus on time-based preventive maintenance (TbPM) without time shifts:* Many existing studies allow flexibility in scheduling PM (e.g., time shifts, varying intervals, age-based replacements). In contrast, the presented model specifically enforces fixed, deterministic periodic intervals for TbPM and no time shifts relative to any previous corrective maintenance events. This constraint (fixed schedule, no time shifts) is a key, yet distinctive modelling assumption.

(2) *Use of the class of Deterministic and Stochastic Petri Nets (DSPNs) for modelling and evaluation*: While many studies use stochastic Petri nets (GSPNs, coloured PNs, hierarchical PNs) or simulation- optimization, fewer focus on modelling a mixed deterministic/stochastic structure (deterministic TbPM schedule + stochastic failures/repairs) using DSPNs under the no-time- shift constraint. This explicit modelling of deterministic scheduling (fixed interval) integrated with stochastic dynamics is less common.

(3) *Numerical steady-state availability evaluation*: This study evaluates system availability as a key performability metric through numerical steady-state analysis of the proposed DSPN model. Unlike prior works limited to conceptual formulations, this approach provides quantitative insights into how stochastic failures, repairs, and fixed-time TbPM jointly affect long-term system availability.

(4) *Application relevance to generic systems requiring high availability under Industry 4.0*: This study explicitly situates the DSPN-based modelling in the context of modern systems (e.g., Industry 4.0, cyber-physical systems, microwave systems). While many prior studies focus on specific application domains such as wind turbines, fleet maintenance, or railway

infrastructure, the present study proposes a generic DSPN-based framework for evaluating TbPM that can be adapted to a broad spectrum of high-availability contexts, including microwave engineering.

(5) *Trade-off analysis between scheduled TbPM and reactive maintenance*: The proposed framework examines the trade-off between pre-scheduled fixed-interval PM actions and reactive (i.e., corrective) maintenance under the constraint of no time shifts, highlighting how this explicit restriction affects system availability.

(6) *Analytical availability approximation*: Closed-form expressions are derived for approximating steady-state availability as functions of MTTF, MTTR, MTPM, and TTPM. These complement DSPN-based simulation by enabling rapid performance estimation and deeper analytical insight into parameter interdependencies, and provide practical guidelines for selecting optimal TbPM intervals across different availability regimes.

Building upon the previous elaboration, the present study advances the existing body of knowledge by formulating a generic DSPN framework capable of capturing the interactions between deterministic TbPM cycles and stochastic failure-repair processes without introducing time shifts of TbPM activities. Such an integrated approach provides a rigorous yet adaptable analytical basis for evaluating system availability and other performability metrics under fixed-schedule maintenance constraints. The following section presents the proposed DSPN model and its structural components in detail.

III. The Proposed DSPN Model

This study employs a Deterministic and Stochastic Petri Net (DSPN) model for preventive maintenance, executed at predefined time intervals without time shifts [12]. DSPNs represent an extended class of Petri nets capable of modelling systems that exhibit both stochastic and deterministic behaviours. In DSPNs, transitions can fire either after random time intervals, typically governed by exponential or general probability distributions, or after fixed, predetermined time delays. DSPNs also support immediate transitions, which fire once they become enabled. This hybrid formalism enables the accurate representation of systems where both random events (such as failures and repairs) and scheduled activities (such as periodic preventive maintenance) occur. Owing to this dual nature, DSPNs are particularly suitable for modelling, simulation, and quantitative evaluation of availability, reliability, and performability in complex discrete-event systems [15–17].

The model, illustrated in Fig. 1, represents a single-component system susceptible to random failures followed by corresponding corrective maintenance actions. The system alternates between two possible states: a working one (a token in the place *P_sys_WORK*) and a non-working one (a token in the place *P_sys_FAIL*). It changes its initial, working state after $1 / \lambda_{sys}$ time units, which represents the mean time to failure (MTTF). The parameter λ_{sys} is the firing rate of the exponential transition *T_sys_MTTF*; the firing of this transition, which is initially enabled, removes the token from the place *P_sys_WORK* and puts it in the place *P_sys_FAIL*. The system stays in this (non-working) state during the corrective maintenance (i.e., repair of the system), which lasts, on average, $1 / \mu_{sys}$ time units, which represents the mean time to repair (MTTR).

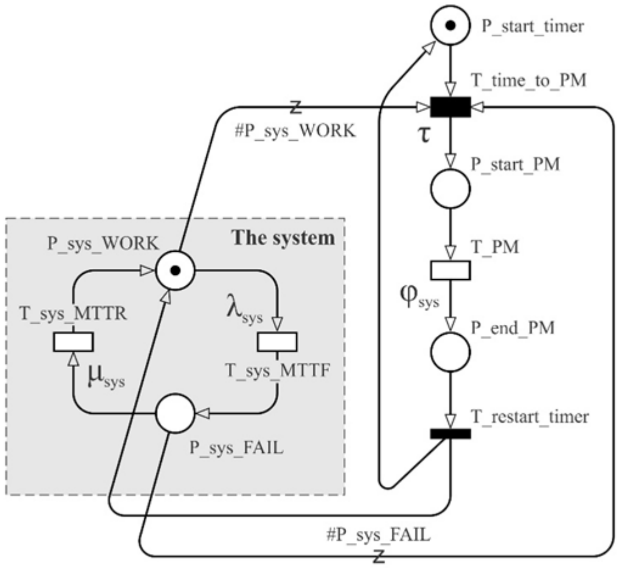

Fig. 1. DSPN model of time-based preventive maintenance without time shifts (Source: Hristoski & Dimovski, 2022 [12])

The parameter μ_{sys} is the firing rate of the exponential transition *T_sys_MTTR*; the firing of this transition, which is enabled when the token resides in the place *P_sys_FAIL*, removes the token from the place *P_sys_FAIL* and puts it back in the place *P_sys_WORK*.

The DSPN model also incorporates a preventive maintenance mechanism, whose activities are pre-scheduled and performed strictly on time, irrespective of whether corrective maintenance has occurred beforehand.

At the beginning, a token resides in the place *P_start_timer*, enabling the deterministic transition *T_time_to_PM*, which fires after τ time units. The parameter τ represents the fixed, pre-determined time to preventive maintenance (TTPM). After τ time units elapse, the deterministic transition *T_time_to_PM* fires, irrespective of any tokens in places *P_sys_WORK* or *P_sys_FAIL*, which are removed because of the arc multiplicities of #P_sys_WORK and #P_sys_FAIL. The system enters a non-working regime, this time because of the ongoing TbPM activities. The firing of the deterministic transition *T_time_to_PM* puts a single token in the place *P_start_PM*, meaning the start of the TbPM activities. This enables the exponential transition *T_PM*, which fires, on average, after $1 / \varphi_{sys}$ time units, which represents the mean time of preventive maintenance (MTPM). The parameter φ_{sys} is the firing rate of the exponential transition *T_PM*. After the exponential transition *T_PM* fires (i.e., when the TbPM cycle is over), the token is removed from the place *P_start_PM* and put in the place *P_end_PM*. This enables the immediate transition *T_restart_timer*, whose firing removes the token from the place *P_end_PM* and simultaneously puts single tokens in places *P_sys_WORK* and *P_start_timer*, thus starting a new TbPM cycle. The time starts elapsing until the next scheduled PM, while the system is considered to be in a working state again, regardless of the state it was before the preventive maintenance occurred.

IV. Model Evaluation

Given that marking M = (#P_sys_WORK #P_sys_FAIL #P_start_timer #P_start_PM #P_end_PM) $\in \mathbb{N}^{|P|}$, where P denotes the finite set of five places in the DSPN model, each component of M is a five-tuple that represents the number of tokens in the corresponding place $p \in P$. Based on this definition, the corresponding Extended Reachability Graph (ERG) can be constructed (Fig. 2). In the ERG, tangible markings in which the deterministic transition is enabled are represented by bold-line rectangles (i.e., M_0 and M_1); tangible markings where only exponential transitions are enabled are shown by regular-line rectangles (i.e., M_2); and the marking M_3, depicted by a dashed-line rectangle, is the sole vanishing marking, where only the immediate transition is enabled.

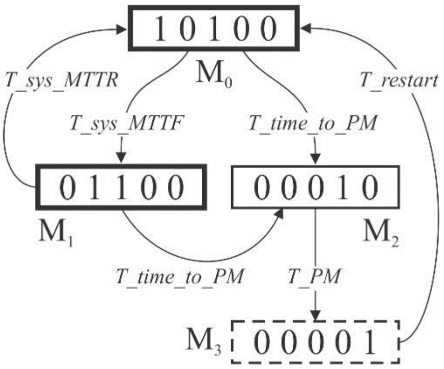

Fig. 2. Extended Reachability Graph (ERG) of the DSPN model (Source: The authors [14])

The corresponding Reduced Reachability Graph (RRG) is derived from the ERG by eliminating vanishing markings, as illustrated in Fig. 3.

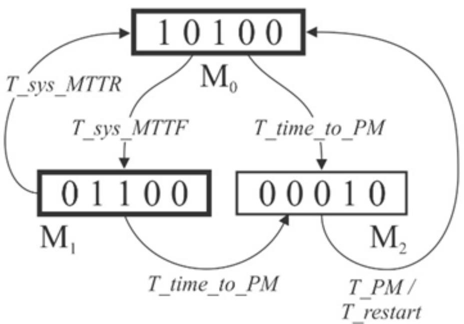

Fig. 3. Reduced Reachability Graph (RRG) of the DSPN model (Source: The authors [14])

It consists of three tangible markings: M_0, M_1, and M_2. Within this framework, knowing that 'P' stands for a probability and '#' signifies the number of tokens in corresponding places, *TimeNET*® allows the definition of the corresponding steady-state probabilities of being in these three tangible markings (π_0, π_1, and π_2), as follows:

- *For marking M_0 (system working, timer waiting)*:
  π_0 = P{(#P_sys_WORK = 1) $\wedge$ (#P_sys_FAIL = 0) $\wedge$ (#P_start_timer = 1) $\wedge$ (#P_start_PM = 0)}
- *For marking M_1 (system failed, timer waiting)*:
  π_1 = P{(#P_sys_WORK = 0) $\wedge$ (#P_sys_FAIL = 1) $\wedge$ (#P_start_timer = 1) $\wedge$ (#P_start_PM = 0)}
- *For marking M_2 (preventive maintenance active)*:
  π_2 = P{(#P_sys_WORK = 0) $\wedge$ (#P_sys_FAIL = 0) $\wedge$ (#P_start_timer = 0) $\wedge$ (#P_start_PM = 1)}

The steady-state probability π_0 denotes the operational state and directly measures system availability, π_1 represents the non-operational state due to failures and corrective maintenance, while π_2 corresponds to downtime caused by scheduled TbPM activities.

The numerical evaluation of the steady-state probabilities π_0, π_1, and π_2, which satisfy $\pi_0 + \pi_1 + \pi_2 = 1$, was performed using the *TimeNET*® software tool. This platform supports the modelling and analysis of various classes of stochastic Petri Nets, including those featuring exponentially distributed, non-exponentially distributed, deterministic, and immediate transition firing times [18–20]. The evaluation was conducted for two representative types of generic systems: one characterized by low availability and the other by high availability. The resulting steady-state probabilities π_0, π_1, and π_2 are determined by, and therefore dependent on, the working parameters of the DSPN model, as summarized in Table 1.

TABLE 1
Steady-state probabilities with low- and high-availability systems: an example (source: the authors [14])

	Low-availability system	High-availability system
MTTF [h]	300	100,000
MTTR [h]	70	0.5
MTPM [h]	5.0	2.5
TTPM [h]	1,000	18,000
π_0	0.8174612696369	0.9998573882315
π_1	0.1775636058639	0.0000049991900
π_2	0.0049751244992	0.0001376125785

A. Low-availability Systems

The steady-state analysis of the DSPN model for a low-availability system was performed using the following key parameter values: a fixed mean time for preventive maintenance (MTPM) of 5.0 h; mean time to failure (MTTF) ranging from 100 h to 500 h in increments of 100 h; mean time to repair (MTTR) ranging from 10 h to 100 h in increments of 10 h; and time to preventive maintenance (TTPM) ranging from 100 h to 1,000 h in increments of 100 h (Fig. 4, Fig. 5).

The plotted surface in Fig. 4 reveals a monotonic, yet nonlinear relationship between availability, MTTF, and TTPM, which can be described as follows:

(a) *Effects of MTTF*: Availability increases markedly with rising MTTF, as longer average times between failures reduce breakdown frequency, allowing the system to remain operational for a greater proportion of its operational lifecycle. The steep gradient along the MTTF axis confirms that MTTF is the dominant factor influencing availability in low-availability regimes.

(b) *Effects of TTPM*: Availability slightly decreases with increasing TTPM, especially at low MTTF values. When failures are frequent (i.e., when MTTF is short), longer maintenance intervals allow degradation to accumulate, increasing unplanned failures and reducing availability. For higher MTTF values, TTPM has a weaker effect, indicating that maintenance timing is less critical in inherently reliable systems.

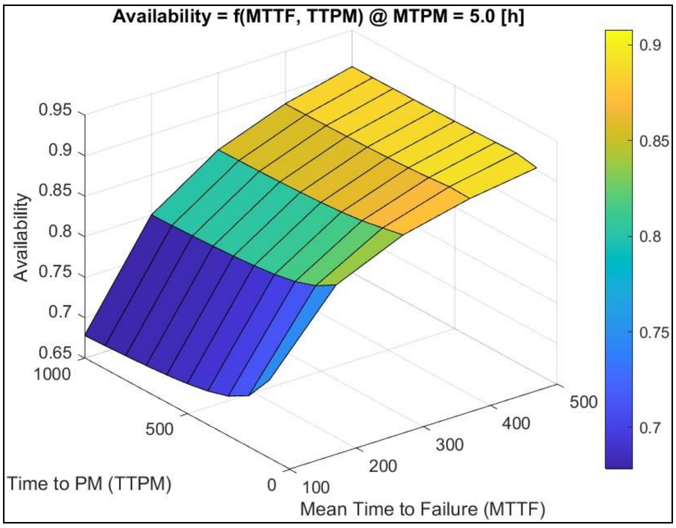

Fig. 4. 3D surface plot showing the availability of low-availability systems versus MTTF and TTPM (Source: The authors [14])

(c) *Combined effects*: The interaction between MTTF and TTPM is nonlinear. At low MTTF values, availability is highly sensitive to TTPM: small increases in maintenance intervals cause sharp drops in availability. As MTTF rises, this sensitivity declines, leading to a plateau where availability becomes nearly invariant to TTPM, reflecting the diminishing benefit of preventive maintenance in highly reliable systems.

(d) *Overall system behaviour*: The availability surface spans roughly 0.65–0.90, indicating a low- to moderate-availability system. Its convex shape shows that TbPM most effectively improves availability when baseline reliability (i.e., MTTF) is modest, with diminishing returns beyond a certain MTTF threshold.

The 3D surface plot presented in Fig. 5 also provides several important insights into the availability behaviour of low-availability systems as a function of MTTR and TTPM, while the MTPM is fixed at 5 hours:

(a) *Effects of MTTR*: Availability declines sharply as MTTR increases, since longer repair times keep the system in a failed state longer, lowering overall availability. The steep MTTR gradient indicates it is a key factor in low-availability regimes, where even moderate MTTR reductions, particularly below 30–40 hours, significantly boost availability.

(b) *Effects of TTPM*: Availability also decreases with increasing TTPM, especially in systems with longer MTTRs. Widely spaced maintenance intervals leave the system exposed to failures longer, increasing unplanned downtime. Shorter TTPM intervals improve reliability through more frequent maintenance, though the effect diminishes when repairs are already quick.

(c) *Combined effects*: The surface shape reveals a nonlinear synergistic interaction between MTTR and TTPM. When MTTR is low, availability remains relatively high regardless of TTPM, making the TbPM timing less critical in fast-repair systems. With higher MTTR, TTPM becomes dominant: longer PM intervals greatly increase downtime, leading to steep availability declines. Thus, reducing MTTR can help offset the negative impact of extended PM intervals.

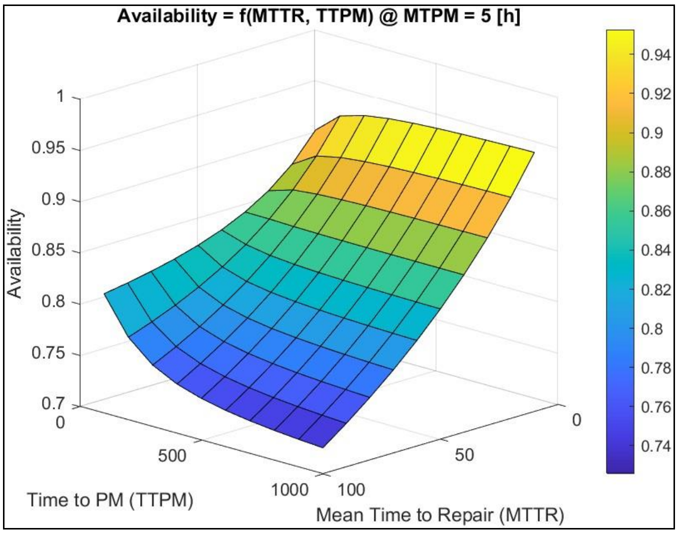

Fig. 5. 3D surface plot showing the availability of low-availability systems versus MTTR and TTPM (Source: The authors)

(d) *Overall system behaviour*: The availability values range roughly between 0.74 and 0.94, characterizing a low- to moderate-availability regime. The convex curvature of the surface implies diminishing returns: as MTTR approaches low values, further reductions yield smaller availability gains. This saturation effect highlights the existence of a practical lower bound for MTTR improvements beyond which PM scheduling exerts greater leverage on system availability.

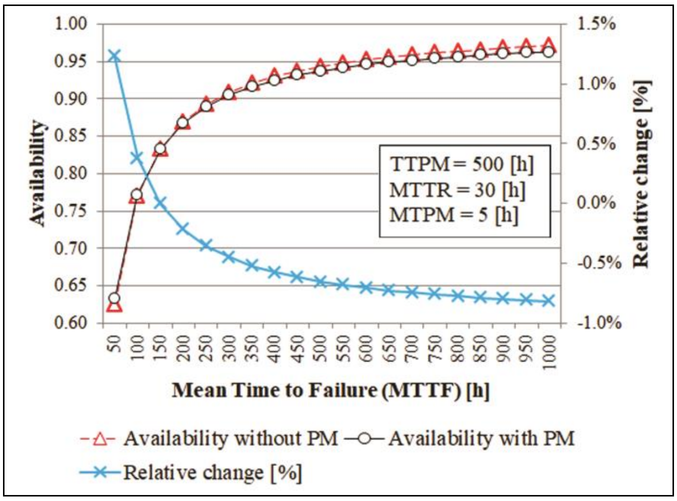

Fig. 6. Comparison of availability levels for low-availability systems with and without TbPM (no time shifts) as a function of MTTF (Source: The authors [14])

A comparison between the system subjected to TbPM without time shifts (for fixed TTPM = 500 h, MTTR = 30 h, and MTPM = 5.0 h) and the system operating without TbPM (for MTTR = 30 h) reveals higher availability levels in the latter case, except when MTTF falls within the range [50; 150] h, i.e., when the ratio MTTF/TTPM ≤ 0.3 (Fig. 6).

B. High-availability Systems

The steady-state analysis of the DSPN model for a high-availability system was performed using the following key parameter values: fixed MTPM = 2.5 h; MTTF ranging from 20,000 h to 100,000 h (step of 20,000 h); MTTR ranging from 0.5 h to 5.0 h (step of 0.5 h); and TTPM ranging from 2,000 h to 20,000 h (step of 2,000 h), as shown in Fig. 7 and Fig. 8.

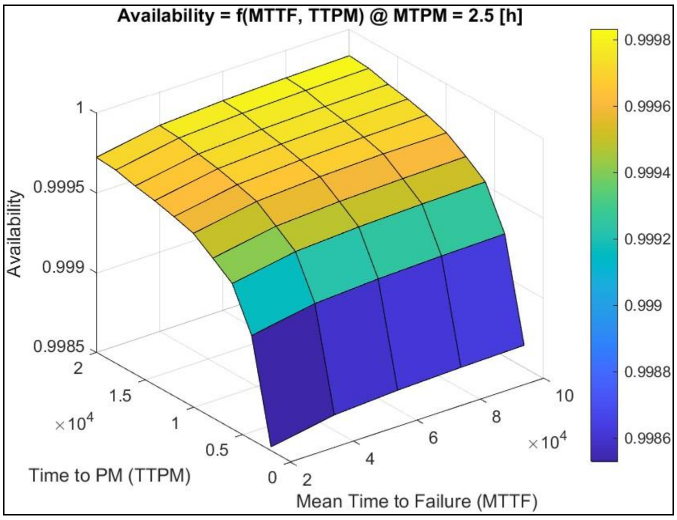

Fig. 7. 3D surface plot of system availability versus MTTF and TTPM for high-availability systems (Source: The authors [14])

The 3D surface plot in Fig. 7 shows system availability as a function of MTTF and TTPM for a high-availability system with fixed MTPM = 2.5 h. The results reveal the relationship between reliability (MTTF) and maintenance frequency (TTPM) in regimes where availability nears unity:

(a) *Effects of MTTF*: As expected, availability increases with MTTF, since less frequent failures yield higher uptime. However, the gradient along the MTTF axis flattens beyond ~60,000 hours, showing diminishing returns: when failures are rare, further MTTF gains have minimal impact. This plateau is typical of high-reliability systems, where maintenance and repair intervals dominate steady-state availability.

(b) *Effects of TTPM*: Availability also increases with longer TTPM intervals, meaning less frequent preventive maintenance yields slightly higher uptime in this high-availability regime. This occurs because short TbPM actions (MTPM = 2.5 h), when performed too often, add excessive planned downtime relative to rare failures. Hence, over-maintenance becomes counterproductive, slightly reducing steady-state availability.

(c) *Combined effects*: The surface shape indicates that MTTF has a dominant influence on availability, while TTPM modulates performance near the high-availability asymptote. The curvature along both axes shows a nonlinear yet monotonic relationship, with no abrupt changes or inflection zones. This suggests the fixed-interval TbPM policy without time shifts remains stable and predictable even in high-reliability contexts.

(d) *Overall system behaviour*: The very narrow high range (≈ 0.9985–0.9999) where plotted availability values lie indicates that the system maintains excellent performance across varying combinations of MTTF and TTPM, corresponding to less than 0.2% downtime, which is typical for mission-critical or industrial automation systems operating in near-continuous service conditions.

The 3D surface plot portrayed in Fig. 8 represents system availability as a function of the MTTR and TTPM, at a fixed MTPM of 2.5 hours, which characterizes a high-availability system.

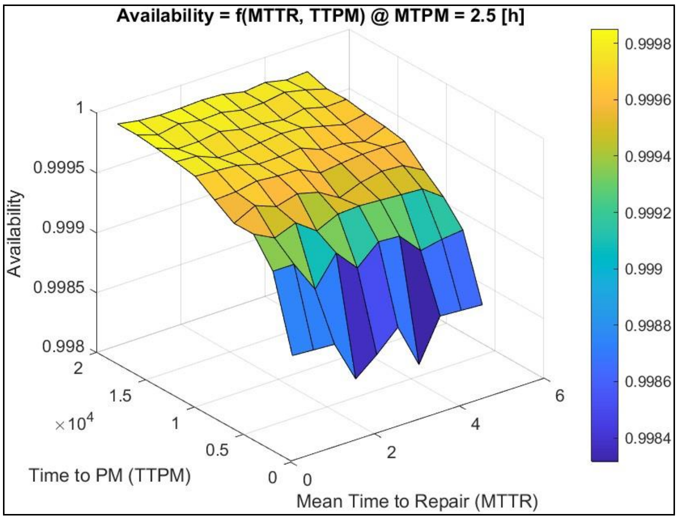

Fig. 8. 3D surface plot of system availability versus MTTR and TTPM for high-availability systems (Source: The authors)

The surface reveals how repair efficiency and preventive maintenance intervals jointly affect overall system uptime when availability levels are near unity:

(a) *Effects of MTTR*: Along the MTTR axis, there is a negligible gradient revealing an inverse relationship between MTTR and availability: as MTTR increases, availability declines. This slope is slightly more evident at lower MTTR values, where faster repairs yield more availability gains. Beyond a certain threshold, the effect tapers off, implying a nonlinear saturation effect typical of high-availability systems.

(b) *Effects of TTPM*: System availability rises with longer TTPM intervals, indicating that overly frequent maintenance slightly reduces uptime due to accumulated planned downtime. Given the short MTPM of 2.5 h, extending TTPM increases productive time without notably raising failure risk. Thus, in highly reliable systems, too frequent TbPM scheduling can be counterproductive, adding downtime with minimal availability benefit.

(c) *Combined effects*: The 3D surface exhibits smooth monotonic curvature, indicating minimal interaction between MTTR and TTPM. Their effects on availability are largely independent: reducing MTTR consistently improves availability across all TTPM values, while extending TTPM provides incremental gains across all MTTR levels. The slight irregularities visible in the surface (minor ridges or nonuniform transitions) may reflect numerical or discretization effects, but they do not alter the overall trend.

(d) *Overall system behaviour*: The surface plot indicates extremely high availability values (≈ 0.9980–0.9999), confirming that the modelled system operates in a high-reliability regime. As stated previously, this corresponds to less than 0.2% downtime, which is typical for continuous-operation systems.

The comparison of availability levels between the system that is subject to TbPM without time shifts (for fixed TTPM = 10,000 h, MTTR = 3 h, and MTPM = 2.5 h) and the system without TbPM (for MTTR = 3 h) reveals higher availability in the system without TbPM across all MTTF values (Fig. 9).

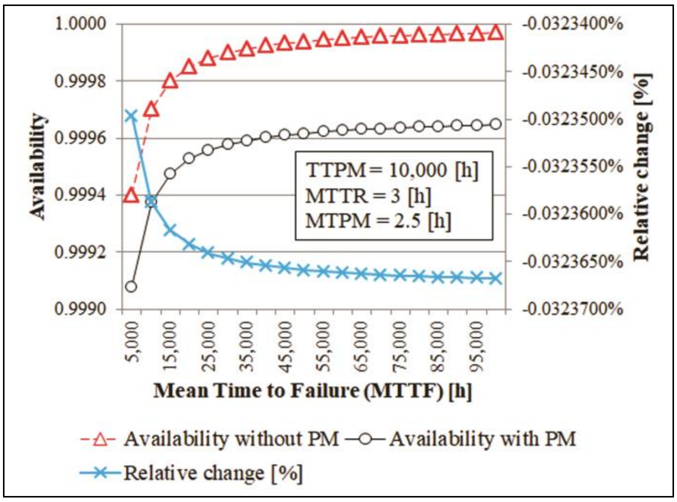

Fig. 9. Comparison of availability levels for high-availability systems with and without TbPM (no time shifts) as a function of MTTF (Source: The authors [14])

V. Analytical Availability Approximation

This section extends the paper beyond simulation-based results by providing analytical insights into how the key working parameters jointly influence system availability. The main contribution lies in developing analytical, closed-form, though approximate, expressions for estimating the steady-state availability as a function of MTTF, MTTR, MTPM, and TTPM with both low- and high-availability systems. To achieve this goal, four simplifying assumptions are taken into account:

(1) For the single-component system modelled by the DSPN, simultaneous failures or repairs cannot occur, since at any given moment it exists in only one of two mutually exclusive states: either operational (subject to random failures), or non-operational (due to corrective repair or a scheduled TbPM). This assumption aligns with the DSPN structure, ensuring that downtime events are sequential (i.e., non-overlapping) in time and additive over the PM cycle;

(2) At most one failure-repair cycle occurs within one TbPM interval, i.e., the system may experience zero or one random failure-repair cycle between any two consecutive TbPM actions, but the probability of having two or more such cycles within the same interval is neglected.
Let the expected number of failures n during the operational portion of a single TbPM cycle be:

$$n = \mathbb{E}\left[N(t)\right] = \mathbb{E}\left[N(TTPM - MTPM)\right] = \lambda \cdot t = \\ = \lambda \cdot (TTPM - MTPM) = \frac{TTPM - MTPM}{MTTF}, \quad (1)$$

where λ = 1 / MTTF is the failure rate, and $N(t)$ is a Poisson random variable counting the number of failures during the operational portion of the TbPM cycle, which lasts for $t = TTPM - MTPM$ time units.
Since failures are modelled as a Poisson process, the probability of observing k failures during t time units is:

$$P(N = k) = \frac{(\lambda \cdot t)^k \cdot e^{-\lambda \cdot t}}{k!}; \; k = 0,\ 1,\ 2, \ldots . \quad (2)$$

So, the probability of observing two or more failures within the same TbPM cycle will be:

$$P(N \geq 2) = 1 - P(N = 0) - P(N = 1) = \\ = 1 - e^{-\lambda \cdot t} - \lambda \cdot t \cdot e^{-\lambda \cdot t} . \quad (3)$$

Given the Taylor expansion of $e^{-\lambda \cdot t}$ and substituting $\lambda \cdot t = n$, if $n \ll 1$ then $P(N \geq 2)$ is negligible. This holds when MTTF ≫ TTPM. Under this assumption, the expected downtime due to random failures per TbPM cycle can be approximated as:

$$D_{FAIL} \approx \lambda \cdot (TTPM - MTPM) \cdot MTTR = \\ = \frac{TTPM - MTPM}{MTTF} \cdot MTTR . \quad (4)$$

This significantly simplifies the analysis by eliminating the need to consider multiple repair cycles or state-dependent residuals within one TbPM interval.

(3) Negligible overlap between repair downtime and preventive maintenance downtime: If a random failure occurs shortly before a scheduled PM action such that the corrective repair overlaps in time with the upcoming PM, this overlap is counted only once in the total downtime of the cycle. The expected duration of such overlap is assumed to be negligible relative to the total TbPM interval. A repair overlaps with the scheduled TbPM if a failure occurs within the last MTTR hours before the TbPM start time. The probability of this event is approximately:

$$P(\text{repair overlaps PM}) \approx \lambda \cdot MTTR = \frac{MTTR}{MTTF} . \quad (5)$$

For most engineering systems, this ratio is much less than 1, so the expected overlap duration is insignificant. Therefore, including or excluding this overlap has an imperceptible effect on the estimated steady-state availability. This assumption allows the expected total downtime D_{TOTAL} in a TbPM cycle to be expressed as the sum of the expected repair downtime D_{FAIL} and the deterministic TbPM downtime *MTPM*, without a correction term for overlapping intervals:

$$D_{TOTAL} \approx D_{FAIL} + MTPM \; . \tag{6}$$

(4) Cycle-based steady-state averaging, which imposes long-run steady-state evaluation over a deterministic TbPM cycle. The time-based preventive maintenance schedule repeats periodically with a fixed cycle length TTPM. In steady state, the long-run availability equals the expected fraction of time the system is operational during one representative cycle:

$$A = 1 - \frac{\mathbb{E}\,[\text{Total downtime per PM cycle}]}{TTPM} \; . \tag{7}$$

Under the ergodic assumption, identical cycles repeat indefinitely with statistically stationary behaviour. This permits the use of the expected-value ratio as a steady-state performance measure, which is a standard approach in availability analysis. This is not a simplification, but a definition of how availability is computed once the expected downtime per cycle has been approximated using the preceding assumptions.

Given the previous, let *a* be the fraction of time lost to TbPM and *b* be the ratio between the repair time and the mean time to failure:

$$a = \frac{MTPM}{TTPM}; \quad b = \frac{MTTR}{MTTF} \; . \tag{8}$$

A. Rare Failures / High Availability

If failures are rare and overlapping repairs are unlikely, the expected total repair downtime per PM cycle will be approximately:

$$\begin{aligned} &\mathbb{E}\left[\text{Repair downtime per PM cycle}\right] \approx \\ &\approx \lambda \cdot \left(TTPM - MTPM\right) \cdot \frac{1}{\mu} \end{aligned} \; . \tag{9}$$

Because failures occur only during operational time (*TTPM* – *MTPM*) and each failure generates a repair of mean duration 1 / μ. Since λ = 1 / *MTTF* and 1 / μ = *MTTR*,

$$\begin{aligned} &\mathbb{E}\left[\text{Repair downtime per PM cycle}\right] \approx \\ &\approx \frac{TTPM - MTPM}{MTTF} \cdot MTTR \end{aligned} \; . \tag{10}$$

Total expected downtime per cycle ≈ downtime due to PM + downtime due to repairs:

$$D_{TOTAL} \approx MTPM + \left(TTPM - MTPM\right) \cdot \frac{MTTR}{MTTF} \; . \tag{11}$$

So, availability per TbPM cycle will be:

$$\begin{aligned} A_{HIGH} &\approx 1 - \frac{D_{TOTAL}}{TTPM} = \\ &= 1 - \left(\frac{MTPM}{TTPM} + \left(1 - \frac{MTPM}{TTPM}\right) \cdot \frac{MTTR}{MTTF} \right) = \\ &= \left(1 - \frac{MTTR}{MTTF}\right) \cdot \left(1 - \frac{MTPM}{TTPM}\right) = \left(1 - b\right) \cdot \left(1 - a\right) \end{aligned} \; . \tag{12}$$

Given the input parameters and simulation result (π_0) in Table 1 for a high-availability single-component system (A = 0.9998573882315), Eq. 12 yields an approximation of 0.9998561118055 (absolute error ≈ –0.0000012764260 ≈ -1.27643×10^{-6}; relative error ≈ -1.27661×10^{-4}%). This approximate result confirms the validity of Eq. 12 to be used for systems where the corrective and preventive downtimes are treated as independent and multiplicative rather than additive contributions.

B. Frequent Failures / Low Availability

When failures are frequent so that the system (between PMs) behaves like an alternating up/down regenerative process, the availability without PM is:

$$A_0 = \frac{MTTF}{MTTF + MTTR} = \frac{1}{1+b} \; . \tag{13}$$

If PM simply removes a fraction *a* = *MTPM* / *TTPM* of calendar time, i.e., PMs reduce the fraction of time the system can be subject to failure proportionally, a first-order approximation is:

$$\begin{aligned} A_{LOW} &\approx A_0 \cdot \left(1 - a\right) = \frac{1}{1+b} \cdot \left(1 - a\right) = \\ &= \frac{MTTF}{MTTF + MTTR} \cdot \left(1 - \frac{MTPM}{TTPM}\right) \end{aligned} \; . \tag{14}$$

Given the input parameters and simulation result (π_0) in Table 1 for a low-availability system (A = 0.8174612696369), Eq. 14 yields an approximation of 0.8067567567567 (absolute error ≈ –0.0107045128802; relative error ≈ –1.30948%). This approximate result confirms the validity of Eq. 14 to be used for systems where repair and failure dynamics dominate total downtime.

VI. Discussion

The results obtained from the DSPN-based evaluation of the TbPM strategy without time shifts offer valuable insights into the dynamic interaction between fixed-time maintenance scheduling and stochastic system failures and repairs. Generally, a system operating under a TbPM regime is expected to demonstrate slightly lower availability than one without preventive maintenance, as each scheduled TbPM session contributes additional downtime. This trend is clearly observable in high-availability systems (Fig. 9). However, in low-availability systems, a different pattern partially emerges: for lower MTTF values, the availability of systems implementing TbPM without time shifts is marginally higher than that of systems operating without PM (Fig. 6). The relative change in availability, expressed in percentages and computed as (*A_with_PM* – *A_without_PM*) / *A_without_PM* × 100, is more pronounced in low-availability systems (Fig. 6) than in high-availability ones (Fig. 9).

This behaviour arises from the complex interplay among MTTF, MTTR, TTPM, and MTPM. Specifically, when MTTF is low but TTPM is relatively high, unplanned failures occur less frequently, reducing the total downtime and improving overall availability. In essence, availability increases when TTPM is properly aligned with MTTF in the following ways:

(a) If TTPM is too short, TbPM actions interrupt system operation excessively, decreasing uptime;

(b) If TTPM is too long, failures tend to occur before TbPM is performed, increasing downtime; and

(c) When TTPM is optimally synchronized with MTTF, the system remains operational for longer periods and experiences fewer failure-repair cycles, resulting in higher availability.

Moreover, the influence of MTTR on availability improvement should not be overlooked:

(a) Shorter MTTR values, reflecting faster repairs, amplify the positive impact of preventive maintenance; and

(b) Even when failures persist, the combination of rapid repairs and well-timed TbPM ensures that the system remains operational for a greater proportion of time.

A noteworthy finding is that system availability exhibits a non-monotonic dependence on TTPM. Specifically, availability increases within certain TTPM ranges but decreases in others. This pattern underscores the complex relationship between the frequency of TbPM interventions and overall system reliability, indicating the existence of an optimal TTPM that maximizes availability while avoiding excessive maintenance actions.

Figure-specific analyses further reinforce these general findings.

In the low-availability regime, Fig. 4 shows that extending the MTTF is the most effective strategy to enhance availability, while shortening the time between preventive maintenance interventions (TTPM) yields noticeable benefits only when failures occur frequently. This underscores the need to tailor maintenance schedules to the system’s inherent reliability characteristics rather than applying uniform time-based intervals. Conversely, Fig. 5 reveals that rapid repair capability, represented by short MTTR, is the single most effective lever for improving availability, particularly when PM occurs at moderate or long intervals. Moreover, combining short MTTR with optimized TTPM yields synergistic effects, significantly improving the system’s uptime. In practice, optimizing repair processes through better spare parts logistics, automated diagnostics, and faster technician response can reduce the need for overly frequent PM, achieving an optimal balance between operational efficiency and system availability.

In the high-availability regime, Figs. 7 and 8 reveal a shift in the dominant factors influencing performance. Fig. 7 confirms that system reliability (MTTF) primarily governs steady-state availability, while preventive maintenance timing (TTPM) plays only a secondary, fine-tuning role. TbPM intervals can therefore be moderately extended without significant availability loss, as long as failures are rare and repairs are efficient. Excessively frequent maintenance yields diminishing returns and may slightly lower availability due to cumulative planned downtime. Therefore, TbPM optimization should balance preventive and corrective maintenance costs rather than pursue minimal downtime through over-scheduling. Practically, improving reliability and repair efficiency provides greater benefits than increasing maintenance frequency. Fig. 8 further confirms that, in high-availability systems with short PM durations, availability depends mainly on repair efficiency, whereas maintenance frequency is secondary. The results indicate that even small reductions in MTTR can yield measurable gains, whereas overly frequent TbPM actions can slightly degrade the system’s availability. Maintenance policies should thus prioritize repair optimization and condition-based scheduling over rigid time-based intervals.

The DSPN-based analysis provides a comprehensive and quantitative foundation for optimizing maintenance strategies across reliability regimes. It demonstrates that minimizing MTTR remains the most powerful means of improving system availability, while TTPM should be fine-tuned to balance preventive and corrective maintenance efforts. The developed model thus offers a robust analytical framework for designing maintenance schedules that achieve high availability with minimal maintenance overhead, an approach particularly valuable in reliability-critical sectors such as power generation, telecommunications, and industrial automation.

The DSPN approach offers a powerful means to assess system availability by integrating both deterministic and stochastic processes within a unified framework. Its graphical formalism enhances transparency and interpretability, while simulation tools such as *TimeNET®* enable quantitative evaluation of various performance measures under various maintenance strategies. However, the usage of DSPNs also faces limitations, such as state-space explosion in complex models and reliance on accurate parameter estimation (e.g., MTTF, MTTR, MTPM, TTPM). Additionally, simplifying assumptions such as constant rates and independence of events may reduce realism. Despite these challenges, DSPNs strike a valuable balance between model expressiveness and computational feasibility, making them well-suited for analyzing both low- and high-availability systems.

VII. CONCLUSION

This study presents a DSPN-based framework for assessing time-based preventive maintenance strategies without time shifts, providing a thorough evaluation of their effects on system availability. Simulation experiments conducted in TimeNET® confirm the theoretical results, showing that availability improves when the preventive maintenance interval (TTPM) is properly adjusted relative to the mean time to failure (MTTF), mean time to repair (MTTR), and mean time of preventive maintenance (MTPM). Conversely, poorly coordinated TbPM scheduling can unexpectedly decrease availability, as excessive maintenance efforts cause unnecessary downtime without significantly reducing failure rates. The observed non-monotonic trends in availability highlight the crucial need to balance preventive maintenance frequency with the system’s inherent reliability and repair characteristics.

Furthermore, the results underline the decisive role of failure and repair parameters in shaping system performance. In high-availability systems (large MTTF, small MTTR), preventive maintenance must be carefully scheduled to prevent disruptions that outweigh its benefits, whereas in low-availability systems, more frequent interventions may still be warranted to prevent major breakdowns. The proposed DSPN model, validated through *TimeNET*® simulations, thus provides a robust analytical foundation for optimizing TbPM policies in reliability-critical domains such as power generation, telecommunication networks, microwave systems, and automated production systems.

From a practical standpoint, the findings demonstrate that minimizing repair time (MTTR) remains the most effective lever for improving availability. At the same time, preventive maintenance intervals should be optimized, not simply shortened, to avoid maintenance-induced inefficiencies. This aligns with Industry 4.0 paradigms, where deterministic TbPM strategies can be complemented by predictive maintenance and real-time system monitoring.

Future research may proceed along several directions. First, identifying the optimal TTPM interval that maximizes availability remains an important extension. Second, incorporating adaptive or condition-based maintenance into the DSPN model would enable real-time adjustment of TTPM using degradation data or sensor feedback. Third, integrating cost and resource constraints, such as workforce, spare parts, or maintenance budgets, would allow balancing availability with operational costs. Fourth, studying multi-component or networked systems could reveal how subsystem interactions affect the overall system's availability and maintenance strategies. Lastly, applying machine learning or reinforcement learning to predict failures and optimize TbPM intervals in real time offers a promising route toward intelligent, self-adaptive maintenance systems.

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