Evaluating the Model of Preventive Maintenance with Time Shifts: A Stochastic Petri Nets Approach

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Abstract. In the Industry 4.0 era, preventive maintenance plays a crucial role in ensuring system reliability and minimizing downtime. Among others, the key reasons include integration of smart technologies, increased system complexity, cost reduction, enhanced productivity and efficiency, and regulatory compliance and safety. In this context, this paper evaluates a Deterministic and Stochastic Petri Net (DSPN) model of a generic system experiencing alternating failures and repairs while undergoing preventive maintenance at regular intervals. Unlike traditional models, the proposed approach incorporates time shifts, where each failure and subsequent repair reset the countdown to the next preventive maintenance. The DSPN framework captures the stochastic nature of failures and repairs alongside deterministic scheduling constraints. Performance evaluation focuses on system availability under two scenarios: a low availability system and a high availability system. The results provide insights into how time-shifted preventive maintenance strategies impact long-term system performance. This study contributes to the overall body of knowledge about optimizing maintenance policies by balancing preventive interventions and corrective actions, supporting enhanced operational efficiency in industrial systems.

Keywords: preventive maintenance · Deterministic and Stochastic Petri Nets (DSPNs) · modeling and simulation · system availability analysis · TimeNET®

1 Introduction

Preventive maintenance (PM) is a strategic, proactive approach designed to minimize the risk of unexpected equipment failures and optimize operational efficiency. As a subset of planned maintenance, PM plays a crucial role in effective asset and facilities management by encompassing a broad spectrum of routine inspections, servicing, and performance assessments. By addressing potential issues before they escalate into costly breakdowns, PM helps industrial organizations enhance reliability, extend asset lifespan, and reduce downtime-related losses [1, 2]. In the Industry 4.0 era, maintenance strategies increasingly leverage Internet of Things (IoT), artificial intelligence (AI), and Big Data analytics

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to enable real-time monitoring and insights into machine health. Predictive and preventive maintenance strategies both help anticipate failures before they occur, reducing unexpected breakdowns and unplanned downtime. On the other hand, modern industrial systems are highly interconnected and automated, making unplanned failures more disruptive, whilst preventive maintenance ensures smooth operation and reduces cascading failures in such cyber-physical systems. Reactive maintenance can be expensive due to emergency repairs, production halts, and damaged components. Preventive maintenance optimizes maintenance schedules, reducing overall costs by expanding asset lifespans. Scheduled maintenance activities prevent unscheduled downtime, improving production continuity and system availability. At last, but not at least, many industries have strict safety and compliance requirements. Preventive maintenance helps meet these regulations, reducing risks to equipment and personnel, thus contributing to better workplace safety. By minimizing waste from unplanned maintenance trips and excessive spare parts inventory, PM also enhances sustainability. By proactively maintaining equipment, organizations can maximize operational efficiency and maintain competitive advantages in the Industry 4.0 landscape [3].

The preventive maintenance based on time, also known as time-based preventive maintenance (TbPM), periodic maintenance, or calendar-based PM, is a proactive preventive maintenance strategy in which equipment is serviced, inspected, or replaced at predetermined intervals, regardless of its actual condition. By adhering to a fixed schedule, TbPM aims to reduce the likelihood of unexpected failures, enhance reliability, and extend asset lifespan. This systematic approach is particularly beneficial for components with predictable wear patterns, where regular upkeep helps maintain efficiency and safety [4]. In the dynamic field of maintenance management, TbPM remains a fundamental and widely adopted strategy for preserving the longevity and performance of machinery and infrastructure. While more advanced, condition-based and predictive maintenance methods have emerged with technological advancements, TbPM continues to serve as a reliable framework, especially in industries where scheduled servicing aligns with operational requirements and regulatory compliance [5].

Recognizing the significance of TbPM in today's highly digitalized environments as well as the importance of availability as one of the most important performability measures, this paper evaluates the impact of one of the TbPM variants on system availability using a Deterministic and Stochastic Petri Net (DSPN) model originally developed and proposed by Hristoski & Dimovski in 2022 [6]. The DSPN methodology was chosen for this study due to its ability to accurately model and analyze complex maintenance processes that involve both stochastic (random) and deterministic (fixed-time) events. This hybrid modeling capability is essential for capturing the realistic behavior of a system undergoing failures, repairs, and preventive maintenance with time shifts. The evaluation of the DPSN model has been carried out using TimeNET®, a software package dedicated to the modeling and evaluation of various classes of stochastic Petri Nets, which support transitions with immediate, exponentially distributed, deterministic, and general firing time distributions [7, 8]. It was selected as the modeling and analysis tool due to its specialized capabilities in handling the class of DSPNs and its well-established use in reliability and availability modeling. The main research question that this study strives to answer is how this specific TbPM strategy affects the availability of a generic system undergoing consecutive corrective maintenance (failures and repairs). This way the study aims to fill the empirical gap by evaluating a realistic DSPN model that captures the time shifts in TbPM of a generic system susceptible to failures and repairs, integrating both stochastic and deterministic dynamics, and evaluating system availability under low- and high-availability scenarios through simulation-based validation using TimeNET®. While various methodologies, such as Markov Chains (MCs) and Semi-Markov Processes (SMPs), Reliability Block Diagrams (RBDs), Fault Tree Analysis (FTA) with time-dependent extensions, Monte Carlo simulations, various mathematical optimization models and most recently, Machine Learning (ML) and predictive maintenance models, have been extensively used for TbPM evaluation, DSPNs offer a unique advantage by combining stochastic failures, deterministic PM, and time-shift effects in a single framework, making them ideal for the study's objectives.

The rest of the paper is structured as follows: Sect. 2 provides a review of recent research on preventive maintenance modeling and evaluation using various classes of stochastic Petri Nets, while Sect. 3 presents the DSPN model and details the methodology used for its assessment. The steady-state analysis of the DSPN model is presented in Sect. 4, whilst the obtained analysis results are discussed in Sect. 5. The last section concludes the study and suggests directions for future research.

2 Related Research

Recent research on various aspects of PM has surged, underscoring the need for more adaptive, data-driven maintenance strategies to enhance reliability, minimize downtime, and optimize costs in Industry 4.0. Various classes of stochastic Petri Nets have been widely employed as robust modeling tools as well as powerful and versatile graphical and mathematical frameworks to analyze a wide gamut of real-world discrete-event dynamic systems, offering valuable insights into the impact of various maintenance strategies on their performability aspects.

Over the past decade, research on maintenance modeling with Petri Nets (PNs) has surged significantly, encompassing a wide range of PN classes, including Generalized Stochastic Petri Nets (GSPNs) [9–11], Colored Petri Nets (CPNs) [12–15], and Deterministic and Stochastic Petri Nets (DSPNs) [16].

Petri Nets were used to model the maintenance activities of wind turbines [9], to model, simulate, and optimize maintenance costs on multiunit systems [10], to model and evaluate the maintenance processes for railway systems [12], in technological facilities [14], for aircraft maintenance [15], to help improve the reliability and availability of an electric power system's infrastructure [17], as well as to plan and optimize maintenance logistics of small hydroelectric power plants [18]. Reference [19] proposed a methodology to properly define the optimal structure and properties of reduced complex Petri Net models used in maintenance modeling. Recently, several DSPN-based models of TbPM strategies have been proposed in [6], whilst a broader overview of various maintenance strategies using the classes of GSPNs and DSPNs was conducted in [20]. An evaluation of the availability of a similar DSPN model for a generic system prone to consecutive failures and repairs, also subject to time-based preventive maintenance but without time shifts, can be found in [21].

3 The DSPN Model

This study utilizes the DSPN model to analyze a preventive maintenance strategy based on predetermined time intervals, while incorporating dynamic time shifts, as initially introduced by Hristoski & Dimovski in 2022 [6]. The model, depicted in Fig. 1, represents a generic system prone to failures that necessitate corrective maintenance actions. In addition to reactive repairs, the system undergoes scheduled preventive maintenance, which is planned at fixed intervals and executed only if corrective maintenance has not already been performed. Notably, in this framework, preventive maintenance cycles are not strictly time-fixed; instead, they are influenced by preceding corrective maintenance activities, leading to shifts or delays in the TbPM schedule. In other words, any corrective maintenance activity resets the PM cycle, causing the next PM to be rescheduled.

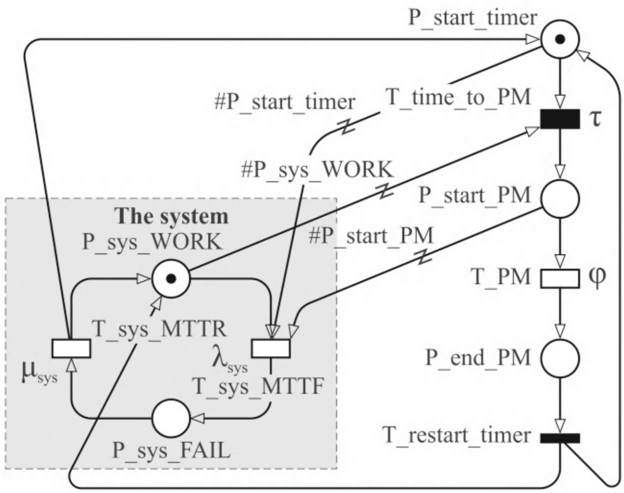


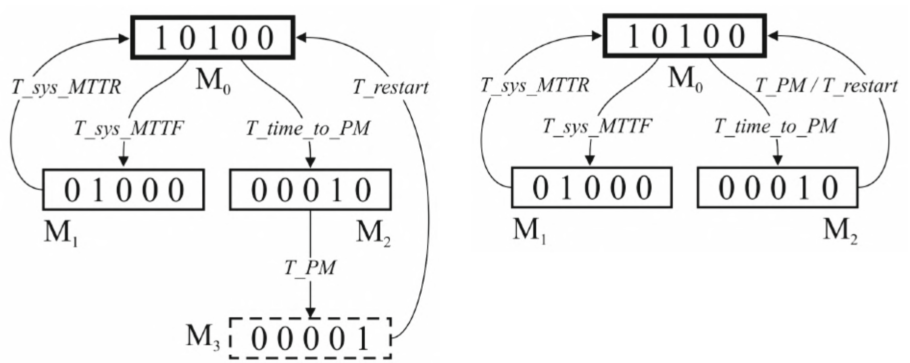
Fig. 1. SDSPN model of a generic system undergoing failures and repairs, which is also subject to TbPM cycles based on pre-determined time intervals with time shifts (Source: The Author)

If a failure occurs (i.e., a token is placed in the place *P_sys_FAIL* after the exponential transition *T_sys_MTTF* fires), the countdown to the next PM session is suspended (i.e., there is no token in place *P_start_timer*). Once the corrective maintenance is completed (i.e., a token is placed back in place *P_sys_WORK* after the exponential transition *T_sys_MTTR* fires), the system returns to an operational state (i.e., there is a token in place *P_sys_WORK*) and, simultaneously, the countdown to the next PM session is restarted (i.e., a token is put in place *P_start_timer*).

If no failure occurs before the scheduled start of the PM session (i.e., a token is removed from place *P_start_timer* and put in place *P_start_PM* after the deterministic transition *T_time_to_PM* fires), a PM session is conducted, lasting on average 1/φ time units, where φ represents the firing rate of the exponential transition *T_PM*. Upon successful completion of the PM session (i.e. a token is put in the place *P_end_PM* after the exponential transition *T_PM* fires), the immediate transition *T_restart_timer* fires, placing a token in place *P_sys_WORK* (i.e., indicating that the system becomes operational again) and also placing a token in place *P_start_timer* (i.e., marking the beginning of a new PM countdown, which will last τ time units unless interrupted by a failure).

4 The Analysis

The marking M = (*#P_sys_WORK #P_sys_FAIL #P_start_timer #P_start_PM #P_end_PM*) is a five-tuple representing the number of tokens in each place in the DSPN model [22, 23]. Figure 2(a) shows the corresponding Extended Reachability Graph (ERG), where the tangible marking when the deterministic transition is enabled, is represented with a bolder-line rectangle (i.e., the initial marking $M_0 = (1\ 0\ 1\ 0\ 0)$), the tangible markings where only exponential transitions are enabled are drawn by regular-line rectangles (i.e., markings M_1 and M_2), while the marking $M_3 = (0\ 0\ 0\ 0\ 1)$, represented by a dashed-line rectangle, shows the vanishing marking when the only immediate transition is enabled. The equivalent Reduced Reachability Graph (RRG), depicted in Fig. 2(b), is derived from the ERG by eliminating the vanishing marking M_3.



(a) Extended Reachability Graph (ERG) (b) Reduced Reachability Graph (RRG)

Fig. 2. DSPN model of a generic system undergoing failures and repairs, which is also subject to TbPM cycles based on pre-determined time, with time shifts (Source: Author's representation)

Given that the RRG is comprised of three tangible markings (i.e., M_0, M_1, and M_2), the corresponding steady-state probabilities π_0, π_1, and π_2, representing the long-run probabilities of the system being in different states, can be defined as joint measures over each tangible marking, as follows:

- The sum of π_0, π_1, and π_2 equals 1.
- For marking M_0 (system working, timer waiting):
  $\pi_0 = P\{(\#P\_sys\_WORK = 1) \wedge (\#P\_sys\_FAIL = 0) \wedge (\#P\_start\_timer = 1) \wedge (\#P\_start\_PM = 0)\}$ is the steady-state probability that the system is operational ($\#P\_sys\_WORK = 1$), so it is directly linked with system availability;

- For marking M_1 (system failed, timer waiting):
  $\pi_1 = P\{(\#P\_sys\_WORK = 0) \wedge (\#P\_sys\_FAIL = 1) \wedge (\#P\_start\_timer = 0) \wedge (\#P\_start\_PM = 0)\}$ is the steady-state probability that the system is in a failure state ($\#P\_sys\_FAIL = 1$), so it is directly linked to system unavailability (i.e., downtime) due to corrective maintenance (i.e., repairs);
- For marking M_2 (preventive maintenance active):
  $\pi_2 = P\{(\#P\_sys\_WORK = 0) \wedge (\#P\_sys\_FAIL = 0) \wedge (\#P\_start\_timer = 0) \wedge (\#P\_start\_PM = 1)\}$ is the steady-state probability that the system is undergoing preventive maintenance ($\#P\_start\_PM = 1$), so it is directly linked to system unavailability due to carrying out PM actions, thus giving insights into PM scheduling efficiency and the impact of PM on availability.

In this context, it is worth noting that the availability of the system equals the steady-state probability π_0, the nonavailability due to system failures equals π_1, whilst the nonavailability due to TbPM activities equals π_2. The total nonavailability of the system equals the sum of π_1 and π_2.

The steady-state analysis of the DSPN model has been conducted with numerical simulations using TimeNET® for two types of generic systems:

- Those exhibiting features of *low availability* (i.e. frequent failures, long repairs), under the following restrictions:

  o Mean Time of Preventive Maintenance (MTPM) = 5 [h] (fixed); in real-world scenarios, it usually takes values from the interval [1; 10];
  p Mean Time to Failure (MTTF) [h] is variable and takes values from the interval [100; 500] with a step of 100 [h];
  q Mean Time to Repair (MTTR) [h] is variable and takes values from the interval [10; 50] with a step of 10 [h];
  r Time to Preventive Maintenance (TTPM) [h] is variable and takes values from the interval [100; 1,000] with a step of 100 [h];

- Those exhibiting features of *high availability* (i.e. rare failures, quick repairs), under the following restrictions:

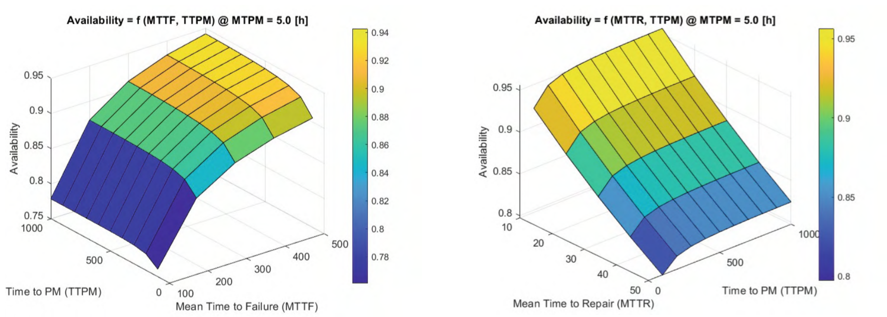
  o Mean Time of Preventive Maintenance (MTPM) = 2.5 [h] (fixed); in real-world scenarios, it usually takes values from the interval [0.5; 5.0];
  p Mean Time to Failure (MTTF) [h] is variable and takes values from the interval [20,000; 10,0000] with a step of 10,000 [h];
  q Mean Time to Repair (MTTR) [h] is variable and takes values from the interval [1; 5] with a step of 1 [h];
  r Time to Preventive Maintenance (TTPM) [h] is variable and takes values from the interval [1,000; 10,000] with a step of 1,000 [h].

4.1 Low-Available Systems

Low-available systems experience frequent failures and require significant corrective maintenance since they operate in harsh environments (i.e., they are continuously exposed to extreme temperatures and dust, debris, and heavy loads that accelerate wear and tear on their mechanical components) or they use aging components/parts. These systems usually achieve availability levels from 60% to 90%.

In the case of low-available systems, the 3D surface plots of how system's availability (Z-axis) depends on MTTF and MTTR (X-axis), and TTPM (Y-axis) given that Mean Time of PM (MTPM) is 5.0 [h], are shown in Fig. 3(a) and Fig. 3(b), respectfully.

The comparison between the achieved availabilities of a low-available generic system, with and without TbPM cycles based on pre-determined time with time shifts, including the availability's relative decrease when TbPM is leveraged, is presented in Fig. 4(a). On the other hand, the graphic presentation of generic system's nonavailability, achieved with and without TbPM cycles based on pre-determined time with time shifts, including the nonavailability's relative increase when TbPM is leveraged, is presented in Fig. 4(b).



(a) Availability = f(MTTF, TTPM) @ MTPM = 5.0 [h]

(b) Availability = f(MTTR, TTPM) @ MTPM = 5.0 [h]

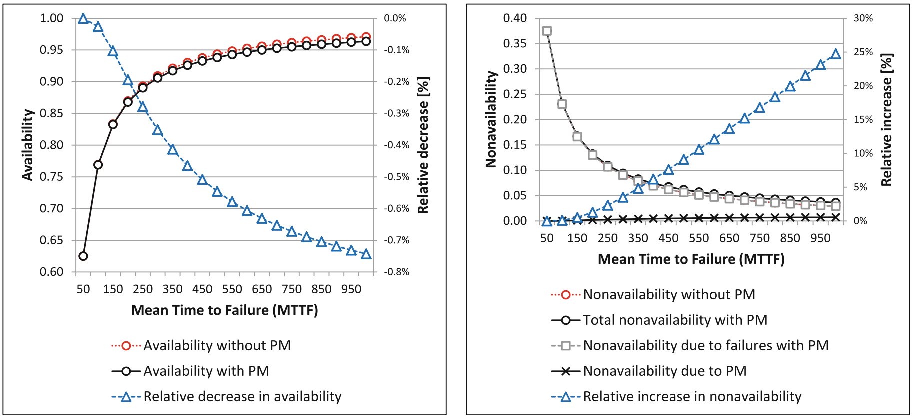
Fig. 3. 3D surface plots of system's availability as a function of (a) MTTF and TTPM and (b) MTTR and TTPM for low-available generic systems undergoing failures and repairs, which are also subject to TbPM cycles based on pre-determined time with time shifts (Source: The author, using TimeNET® simulation results and MATLAB® 3D graphics)

4.2 High-Available Systems

Contrary to low-available systems, high-available systems are designed for minimal downtime, often featuring redundancy, advanced monitoring, and fast maintenance strategies, usually achieving availability levels from 99% to 99.999%.

In the case of high-available systems, the 3D surface plots of how system's availability (Z-axis) depends on MTTF and MTTR (X-axis), and TTPM (Y-axis) given that Mean Time of PM (MTPM) is 2.5 [h], are shown in Fig. 5(a) and Fig. 5(b), respectfully.

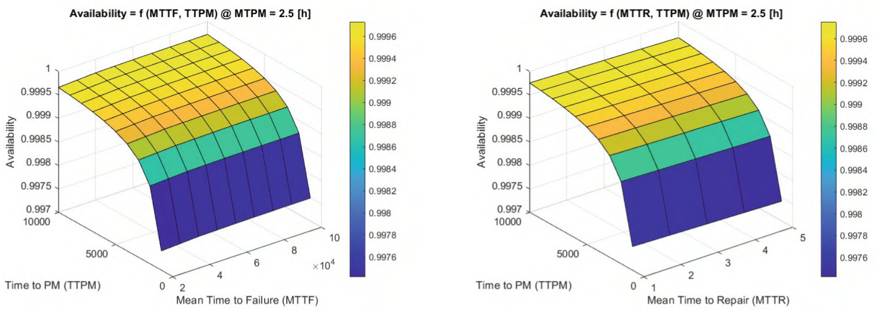
The comparison between the achieved availabilities of a high-available generic system, with and without TbPM cycles based on pre-determined time with time shifts, including the availability's relative decrease when TbPM is leveraged, is presented in Fig. 6(a). On the other hand, the graphic presentation of generic system's nonavailability, achieved with and without TbPM cycles based on pre-determined time with time shifts, including the nonavailability's relative increase when TbPM is leveraged, is presented in Fig. 6(b).



(a) Availability = f (MTTF) @ MTPM = 5.0 [h], TTPM = 500 [h], and MTTR = 30 [h]

(b) Nonavailability = f (MTTF) @ MTPM = 5.0 [h], TTPM = 500 [h], and MTTR = 30 [h]

Fig. 4. Comparison between the achieved availability with and without TbPM for low-available generic systems undergoing failures and repairs, which are also subject to TbPM cycles based on pre-determined time with time shifts (Source: The author, using TimeNET® simulation results)



(a) Availability = f (MTTF, TTPM) @ MTPM = 2.5 [h]

(b) Availability = f (MTTR, TTPM) @ MTPM = 2.5 [h]

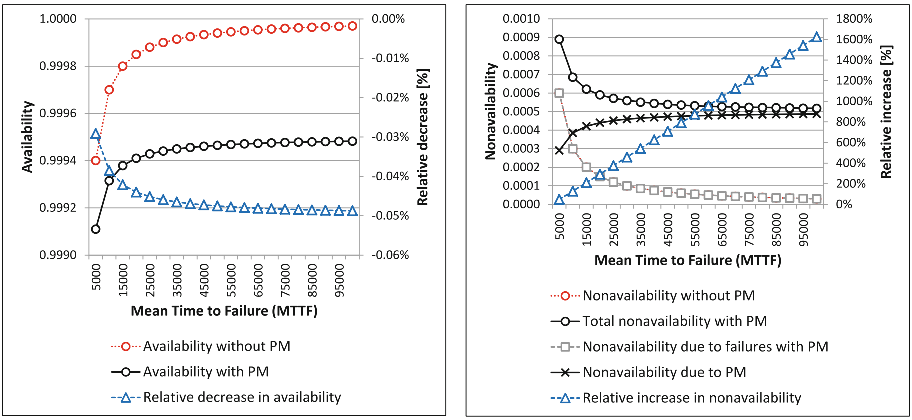
Fig. 5. 3D surface plots of system's availability as a function of (a) MTTF and TTPM and (b) MTTR and TTPM for high-available generic systems undergoing failures and repairs, which are also subject to TbPM cycles based on pre-determined time with time shifts (Source: The author, using TimeNET® simulation results and MATLAB® 3D graphics)

5 Discussion

The verification of the DSPN model has been carried out using the TimeNET®'s *Token Game* module, which confirmed the logical correctness of the proposed model. However, the validation process has not been carried out due to the lack of real-world empirical data on failure rates, repair times, and preventive maintenance schedules for a real-world system for comparison. Besides, the validation of DSPN models is quite challenging because they involve random events. On the other hand, conducting real-world experiments to validate the model would require monitoring an operational system for a long period, gathering detailed maintenance and failure logs, and performing statistical analysis to compare observed *vs.* simulated results, an approach that may not be feasible due to high costs, operational risks, and long timeframes.

Simulation results have confirmed the expected real-world behavior related to system's availability as a feature dependent on variable parameters such as MTTF, MTTR, and TTPM. Assuming a constant/fixed MTPM, in the both cases referring to the assessment of generic low- and high-available systems' availability that alternate between two possible states (i.e., operational and non-operational due to failures), which are also subject to TbPM that is scheduled at variable time intervals (i.e., TTPM) that can be postponed/restarted after the end of each corrective maintenance action (i.e., failure and repair), the availability exhibits the following behavior, evident from Fig. 3 and Fig. 5:

- For fixed MTTF and MTTR, the availability increases as TTPM increases;
- For fixed MTTR and TTPM, the availability increases as MTTF increases;
- For fixed MTTF and TTPM, the availability decreases as MTTR increases;



(a)
Availability = f (MTTF) @ MTPM = 2.5 [h], TTPM = 5,000 [h], and MTTR = 3 [h]

(b)
Nonavailability = f (MTTF) @ MTPM = 2.5 [h], TTPM = 5,000 [h], and MTTR = 3 [h]

Fig. 6. Comparison between the achieved availability with and without TbPM for high-available generic systems undergoing failures and repairs, which are also subject to TbPM cycles based on pre-determined time with time shifts (Source: The author, using TimeNET® simulation results)

Comparing the results presented in Fig. 4(a) for low-available systems and those presented in Fig. 6(a) for high-available systems, it is evident that, despite the bigger MTTF step of 5,000 [h] for high-available systems *vs.* MTTF step of just 50 [h] for low-available systems, the relative decrease [%] of availability due to the introduction of TbPM with time shifts strategy is bigger with low-available systems, where the values are in the range [−0.00028%; −0.774274%], rather than the relative decrease [%] of availability with high-availability systems, where the values are in the range [−0.02907%; −0.04873%]. This is a direct consequence of several factors relevant to low-available systems, such as the higher failure frequency, greater sensitivity to additional downtime, and stronger effects of time shifts resetting the TbPM cycle.

Figures 4(b) and 6(b) refer to the nonavailability of low- and high-available systems, respectively. As expected, in both cases, nonavailability generally decreases as MTTF increases, regardless of whether the system undergoes TbPM with time shifts or it is a subject to corrective maintenance only. The nonavailability due to PM is more emphasized with low-available systems, where it spans a much wider range as compared to high-available systems (i.e., [0.0000028; 0.0074] *vs.* [0.00029; 0.00049]). This indicates a higher relative impact of TbPM with time shifts strategy on low-available systems. For high-available systems, the nonavailability due to TbPM remains within a much narrower range, i.e. from 0.00029 to 0.00049, which suggests a lower absolute impact on high-available systems. The findings also reveal a counterintuitive trend: the relative increase in nonavailability [%] due to introducing TbPM with time shifts strategy is significantly greater for high-available systems, where any increase, even if minor in absolute terms, magnifies the relative impact. This suggests that while TbPM with time shifts remains a viable strategy, its efficiency strongly depends on the system's reliability characteristics. For low-available systems, alternative maintenance approaches might be more beneficial to avoid excessive downtime caused by frequent cycle resets.

6 Conclusion

This study contributes to the field of PM strategies by modeling and analyzing a DSPN framework that incorporates time shifts in TbPM, which represents a novel extension beyond traditional maintenance modeling. By capturing the interplay between failures, repairs, and dynamic PM scheduling, this approach provides a more realistic representation of system behavior, emphasizing the power of DSPNs over other alternative methodologies due to their ability to simultaneously integrate stochastic failures and repairs, deterministic PM, and its time-dependent shifts into a single model. Future research directions, among others, include: (a) empirical validation of the DSPN model by conduct real-world case studies using historical maintenance data from real-world industrial systems; (b) optimization of maintenance policies by developing cost-optimized TbPM strategies that balance availability and maintenance costs; (c) extending the current DSPN framework to address multi-component or networked systems, where failures in one unit may affect others and then analyzing dependency-aware maintenance policies, considering cascading failures; and (d) applying the DSPN model to critical infrastructures to tailor TbPM strategies to industry needs. By addressing these future research directions, the proposed DSPN-based approach can evolve into a robust decision-support tool, enhancing both theoretical contributions and practical implementations in PM planning. Overall, this research provides valuable theoretical and simulation-based insights into time-shifted PM strategies, offering a solid foundation for future studies and practical applications in industries where system uptime is critical.

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