5th Asia Pacific Conference on Industrial Engineering and Operations Management
Tokyo, Japan, September 10-12, 2024
Publisher: IEOM Society International, USA DOI:10.46254/AP05.20240247
Published: September 10, 2024

Maximizing System Availability Subject to Budget Constraints Using a Markov Decision Process (MDP) Model

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Abstract

Maintaining the industrial system in high availability is particularly crucial and significant in production processes, which in turn affect profitability. This paper will develop a new Markov Decision Process model for system availability optimization under budget constraints. The primary objective will be to optimize long-run availability, meaning maximization of expected system uptime at minimum cost of operation per unit time. Given the dual objectives, our model will focus on availability and consider the cost as one of its constraints. Such a model provides practical maintenance decision-making by integrating real-world data within the MDP framework. We solve the proposed model using linear programming, and results show a balance between system performance and financial sustainability. Further challenges remain in the estimation of the parameters of the system accurately. In this respect, future work is needed to enhance the robustness and adaptability of the model to handle such complex systems in real-time environments.

Keywords
1. Markov Decision Process, 2. Availability, 3. Maintenance, 4. Budget Constraint, 5. Sustainability in Maintenance.

1.Introduction
Industrial operations need very high levels of system availability to maintain efficient. High system availability ensures dependability and operational reliability, which are the key concerns in manufacturing and production industries. However, such availability requires an optimal methodology that balances frequent uptime with budgetary limitations. Inadequate budget allocations for maintenance lead to considerable losses due to downtimes, while excessively high budgets have led to inefficient use of resources. Maintenance operations should therefore be optimized in such a way that it results in maximum availability of the system within the budgetary limits. This study aims to develop strategies for optimizing maintenance that will enhance system availability and ensure financial sustainability in an industrially demanding environment.

The purpose of the present work is to develop an MDP model and apply it to obtain the optimal maintenance plan. In particular, the study focuses on investigating the maintenance decision that would lead to maximum system availability through different states. The rest of the paper is organized as follows: Section 2 reviews the literature relating to MDP models in maintenance optimization. Section 3 introduces the proposed MDP model which attains maximum system availability within a budget constraint, while Section 4 describes the solution methodology and results discussion. Finally, Section 5 outlines the conclusions drawn from this research.

2. Literature Review
Availability known as the ability of a system to perform its required function in given conditions up to a given point in time or during a given time interval (Lazzaroni et al. 2011). The availability term in maintainability engineering refers to the quality of service of the system and it is calculated as a percentage of actual working time to the total time according to (Djenadic et al. 2019). Availability it is also a concept used to characterize the performance of a machine, component, or system concerning its ability to fulfill its intended function (Zio et al. 2010). It is an overall indicator that includes partial indicators related to reliability, maintenance, and performance.

Condition-based maintenance (CBM) is a strategy that aims to maximize system availability by making maintenance decisions based on the condition of the system. CBM takes the availability and safety of a system as priorities by considering them when making maintenance decisions (Fallahi et al .2022). In CBM, real-time sensor data for condition monitoring of the system is utilized where condition monitoring, CM, is applied (Kumar et al .2023). Using CM would allow the provision of insights to machine operators on how asset failure risks for machines evolve, and enable them to optimally schedule their maintenance and improve their availability (Dziula et al. 2022).

The semi-Markov approach is, however, implicated as an appropriate model in which complex mechanical systems deteriorate with age and for assessing the availability of such a system (Li et al. 2021). Generally, multistate models are adopted in analyzing machine availability about inspection, repair, and degradation (Ghandali et al. 2018). By combining these approaches, maintenance policies can be determined to maximize system availability and profitability. Overall, CBM strategies allow for proactive and effective maintenance actions; this results in improved system availability. A number of papers have focused on the optimization of availability for repairable systems with a preventive maintenance policy." (Zhixia et al. 2013) developed a mathematical model and derived the steady availability formula for deteriorating systems. (Xu et al., 2008) considered both preventive and corrective maintenance and used strong continuous semi-group theory to determine the steady availability of deteriorating equipment. (Samet et al., 2009) developed a mathematical model to study the evolution of system availability proposed a preventive maintenance strategy for a single-unit system and developed a mathematical model to study the evolution of system availability. (Udoh et al. 2020) proposed a complementary optimal age maintenance policy for repairable systems to achieve high availability and safety standards. (Costar et al. 2015) discussed the determination of an optimal maintenance policy for a repairable system with a constant repair rate and linearly increasing hazard rate. These papers provide insights into optimizing availability through preventive maintenance strategies for repairable systems.

The MDP models have predominantly been applied to dynamic maintenance optimization because these models can accommodate sequential decision-making under uncertainty(Alagoz et al. 2010; White & White 1993). The models provide a systematic framework for determining optimal maintenance policies through comparisons of long-term benefits and costs accrued through different actions and system states. The capability of considering a dynamic environment and evolving systems, and simultaneously or subsequently the effects of maintenance actions taken on system conditions, makes MDPs very valuable in many applications.

One of the key strengths of an MDP model is the ability of the model to capture risk awareness in the process of making maintenance decisions. Because several factors may be made in regard to safety and reliability, MDP models ensure that the maintenance policies developed are both effective in performance and meet the required levels of safety.For instance, SMDPs are an extension of MDPs to include randomness associated with the timing of decision points and are thus particularly applicable to CBM strategies where decisions are triggered by the state of the system rather than at fixed intervals (Chen and Trivedi 2005). present some techniques for overcoming the computational difficulties inherent in solving MDPs in the context of maintenance optimization:

Dynamic Programming and Bellman Equations: DP is an approach in which the solution to MDPs is based on iteratively calculating value functions using Bellman equations. Although highly effective in solving problems where the state spaces are manageable, DP becomes impractical if the size of the state space increases excessively (Gosavi, 2014; White & White, 1993; Aldurgam & Elshafei 2010). This limitation thus instigates the need for approaches other than those used within large-scale systems.

LP represents a far more scalable approach, especially in the case when an MDP is constrained due to the inability of traditional dynamic programming methods. LP methods can embed other operational constraints like safety, reliability constraints, and budget limits with ease, hence they are more captivating in maintenance optimization problems (Xu et al. 2021; Zadorojniy & Shwartz 2006). However, most developed henceforth LP-based methods assume that system parameters are static. This is likely to limit its efficacy in a dynamic environment.

Approximate Dynamic Programming: For large or continuous state space MDP problems, ADP methods provide a practical solution by approximating value functions for such huge solution spaces. Techniques, which include value iteration and Q-learning can often be simulation-based and provide ways of dealing with a complex system that otherwise would be computationally intractable (Gosavi 2014; Ahluwalia et al. 2021).

Monte Carlo Simulation: The various scenarios that the system undergoes are simulated using the Monte Carlo method; these are approximate expected costs of various maintenance strategies. This approach is particularly useful when dealing with systems possessing a high degree of stochasticity, for which an explicit analytical solution may be difficult to obtain (Kim et al. 2015; Cohen & Parmentier 2018).

Policy Iterations: An initial arbitrary policy is progressively improved iteratively by interleaving between the processes of policy evaluation and policy improvement until an optimal solution can be realized. This is more amenable when the state and action spaces are well-set with system dynamics that are well comprehended (Alagoz et al. 2010; Brooks & White 1989).

Multi-Agent Systems and Distributed Optimization: In the case of systems with many interacting sub-components, MDPs can be combined with multi-agent systems in seeking distributed optimization. Frequently, every agent solves a local MDP, while coordination among such agents leads to global system optimization. The above-mentioned methods bear special relevance to applications such as aero-engine maintenance, where several subsystems are to be controlled simultaneously (Wang et al. 2008 and Legay et al. 2013).

In the rest of the sections, we define our new MDP framework that maximizes system availability with budget constraints. Our methodology is based on basic techniques that have been discussed in the literature to develop quite a practical and dynamic approach to industrial maintenance within an uncertain environment that keeps on changing.

3.MDP Model

This section presents a novel MDP model to maximize systems availability subject to budget constraint. An MDP is defined by the tuple $< S, A, P, R, T >$, where:

I. T denotes the planning horizon, which can be either finite or infinite, and encompasses time epochs t.
II. S represents the set of potential system states.
III. A is the set of actions available to the decision maker at discrete time points within T.
IV. P represents the collection of Markovian transition probability matrices that correspond to

different actions.

V. R indicates the reward obtained from taking action a at time t when the system is in state s. The reward may depend on the initial and/or future system states and can be either deterministic or stochastic.

The MDP model for maximizing system Availability for a single machine is formulated as follows:

3.1 Decision/time epochs ($t \in T$):

Our analysis assumes an infinite time planning horizon of T. In this paper, without loss of generality, a day is the time epoch.

State space (S_t): At each decision epoch, the system is fully described by its state, S, the state of the system represents different levels of the machine's deterioration:

S_1: As good as new (high availability level)
S_2: Slightly deteriorated (moderate availability level)
S_3: High deterioration level (low availability level)
S_4: Failed/Down (system is down)
The state space S is represented as:

$$\boldsymbol{S} = \{ S_1, S_2, S_3, S_4 \}$$

These states represent different conditions of the machine, which are inversely proportional to the machine availability.

3.2 Action Space (A)

Each day, the decision-maker relies upon the system state vector $\boldsymbol{S}$ at the beginning of day t. In light of the state information, the decision-maker undertakes the appropriate maintenance action. The maintenance actions in our model are:

$$A = \{ a_0, a_1, a_2\}$$

Where:
a_0: Do nothing
a_1: Minimal repair
a_2: Major repair (restores the system to S1 and is only applicable in S4)

3.3 Transition Probabilities $P(s' \mid s, a)$

The system's transitions from one state to another are dependent on both the state and the action taken. Specifically, $P(s' \mid s, a)$ defines the probability that the system moves to state s' 'given that was in state s and action a was taken. These transition probabilities, for action a, can be represented in matrix form as $\boldsymbol{P_a}$.

3.4 Reward Criteria ($R(S)$ and $C(s, a)$)

The decision-maker aims to maintain the machine in its optimal state to maximize availability. Since different machine states correspond to varying levels of degradation, availability decreases as the machine's condition deteriorates. Therefore, not all operational states equally contribute to the machine's availability. This relationship is represented by $R(S)$, where the availability reward is assumed to depend on the machine state. In addition to the state-dependent reward, maintenance incurs a cost, representing a secondary objective for the decision-maker. Thus, we define a state-action dependent cost, denoted by $C(s, a)$, which captures the cost of taking action a in state s. To achieve the secondary objective, we assume that costs must not exceed a given budget. Since the planning horizon is infinite, the budget is defined as the cost rate in our model.

4. Numerical Analysis

This section presents a numerical example that illustrates the model developed earlier in Section 3.

Demonstrative example

Consider a machine that can exist in various states. State 1 represents a new system, while State 4 represents a failed system. The intermediate states correspond to different levels of deterioration. Three maintenance actions are considered:

I. Do Nothing (a_0): This action maintains the system in its current state or allows it to transition to a worse state.
II. Minimal Repair (a_1): This action either preserves the current state or improves the machine's condition.

III. Major Repair (a_2): This action is only applicable when the machine is in State 4, i.e., failed or down, and it restores the machine to an "as good as new" state.

The transition matrices for these actions are given next:

$$P_{a_0} = \begin{pmatrix} 0.9 & 0.1 & 0.0 & 0.0 \\ 0.0 & 0.8 & 0.2 & 0.0 \\ 0.0 & 0.0 & 0.7 & 0.3 \\ 0.0 & 0.0 & 0.0 & 1.0 \end{pmatrix};\ P_{a_1} = \begin{pmatrix} 0.9 & 0.1 & 0.0 & 0.0 \\ 0.2 & 0.7 & 0.1 & 0.0 \\ 0.0 & 0.3 & 0.6 & 0.1 \\ 0.0 & 0.0 & 0.4 & 0.6 \end{pmatrix};\ P_{a_2} = (1.0 \quad 0.0 \quad 0.0 \quad 0.0)$$

At discrete points in time, the decision-maker must select one of the maintenance actions to maximize the expected availability. Additionally, the average maintenance cost shouldn't not exceed a predefined budget. Since maximizing availability is the primary objective, the budget will be treated as a constraint. Thus, the expected maintenance cost per unit of time must not exceed the budget. The expected availability levels and maintenance costs are presented next.

R(S1) = 100%, R(S2) = 75%, R(S3) = 50%, R(S4) = 0, C(S1, a0) = 0, C(S1, a1) = 1000, C(S1, a2) = N/A, C(S2, a0) = 0, C(S2, a1) = 2000, C(S2, a2) = N/A, C(S3, a0) = 0, C(S3, a1) = 3000, C(S3, a2) = N/A, C(S4, a0) = 0, C(S4, a1) = N/A, C(S4, a2) = 8000.

5. Methodology

In this section, linear programming is employed to determine the optimal policy for the infinite horizon MDP example provided in section 4.1. This method is particularly effective for constrained MDPs where safety or reliability constraints are considered (Xu et al., 2021; Zadorojniy & Shwartz, 2006). To solve the model, we define the decision variable y_i^k, which represents the probability of taking a decision k in state i. The LP is formulated as follows:

Maximize:
$Z = 100\sum_{k=1}^{2} y_1^k + 75\sum_{k=1}^{2} y_2^k + 50\sum_{k=1}^{2} y_3^k$
This function aims to maximize the expected reward by prioritizing decisions that keep the higher reward states.

Constraints:
1. Normalization Constraint:

$$\sum_k \sum_i y_i^k = 1$$

This constraint ensures that the total probability across all states and actions sums to 1.

2. State Transition Constraints:
- State 1:

$$\sum_{k=1}^{2} y_1^k - \sum_{i=1}^{4}\sum_{k=1}^{2} y_i^k P_{i1}^k = 0$$

- State 2:

$$\sum_{k=1}^{2} y_2^k - \sum_{i=1}^{4}\sum_{k=1}^{2} y_i^k P_{i2}^k = 0$$

- State 3:

$$\sum_{k=1}^{2} y_3^k - \sum_{i=1}^{4}\sum_{k=1}^{2} y_i^k P_{i3}^k = 0$$

- State 4:

$$\sum_{k=1}^{2} y_4^k - \sum_{i=1}^{4}\sum_{k=1}^{2} y_i^k P_{i4}^k = 0$$

3. Budget constraint:

$$\sum_k \sum_i C(i,k) y_i^k \leqslant \text{Budjet}$$
$$= 1000y_1^1 + 2000y_2^1 + 3000y_3^1 + 8000y_4^2 \leqslant 1000$$

4. Nonnegativity:

$$y_{ik} \geq 0 \text{ for } i = 0 \ldots M; k = 1,2, \ldots . K$$

6. Results and Discussion -

Excel Solver was used to solve the model in Section 4.2, yielding the results in Table 1:

Table 1 Solution of the MDP model

State i	Decision k	Optimal y_i^k	Optimal Action
1	Do nothing (1)	0.638	1
1	Minimal repair (2)	0	0
2	Do nothing (1)	0	0
2	Minimal repair (2)	0.284	1
3	Do nothing (1)	0	0
3	Minimal repair (2)	0.071	1
4	Do nothing (1)	0	0
4	Major repair (3)	0.007	1
$Z = 88.65\%$			

The implementation of the MDP model using linear programming successfully identifies the optimal maintenance policy for maximizing system availability. The results show that the best policy gives high priority to actions maintaining the system in high-availability states when a minimal repair policy can be implemented. That is confirmed by Table (1), when the system in a high-availability state (S1), the optimal decision rule would be to keep availability as high as possible without taking unnecessary interventions by choosing the action "do nothing," since it minimizes the cost of maintenance.

In the S2 state, when it is slightly deteriorated, minimal repairs should be performed, and they can be refined to assure cost-effectiveness. When deterioration has worsened—that is, in the S3 state—minimal repairs are also quite critical to prevent the system from failing. A major repair is required once it reaches the state of failure, S4, to get the system up again at full efficiency.

The results show that although the cost of minimal repair is the lowest compared to other repair options, it is not the most profitable repair policy as the system availability cannot be brought back to its perfect state. Major repairs, although expensive, will be cost-effective when the loss due to the failure of systems involves more delay and financial losses. The linear programming solution includes budget constraints that guarantee the proposed policies are financially feasible. It means the optimum policy that keeps the budget while maximizing the system availability and managing the financial resources appropriately to maintain high performance levels.

7. Conclusion

The study presents an integrative method to optimize maintenance scheduling in the MDP model for industrial systems under budget constraints and proposes an effective maintenance policy that balances system availability against budget limits under uncertainty. Because the model adapts to changes in the system, it minimizes the occurrence of financial risks due to over-maintenance or under-maintenance. Hence, it has practical applicability in real-world maintenance decision-making. The primary issue here is that it is quite hard to correctly estimate the transition probabilities between system states, and for that purpose, lots of data are to be collected. Besides, it is assumed that the budget is fixed, while under normal conditions, production equipment is exposed to an increased failure rate with time. These two challenges indicate the directions for further research.

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