

Prescriptive Maintenance Planning under Circularity and Operational Constraints over a Finite Horizon

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Maintenance optimization is crucial in industrial systems to ensure reliability and reduce unexpected failures. This work develops a finite-horizon maintenance policy for a single-component system under multiple operational constraints. Circularity is considered via remanufactured replacements, availability constraints ensure decisions respect stock levels, and customer constraints are modeled through time-dependent costs. The approach integrates these aspects in a unified dynamic programming framework, determining optimal actions including component type and maintenance timing. The originality lies in combining multiple constraint types in a single model and translating a practical industrial problem into an implementable policy. Simulation results are also presented to illustrate the model's performance and enable sensitivity analysis with respect to key parameters.

Keywords: Time-varying maintenance costs, Dynamic programming, Remanufacturing, Condition-Based maintenance, Spare parts availability.

1. Introduction

Maintenance planning is essential for operational efficiency and reliability Bouvard (2010). Optimized strategies reduce unexpected breakdowns and improve service. Vehicle manufacturers increasingly use predictive maintenance tools to anticipate failures and optimize replacements. This work, in collaboration with Volvo Group, integrates real-world constraints into deployable maintenance strategies: circularity via remanufactured components, stock availability, and customer-imposed maintenance restrictions. Existing models typically address only subsets of these constraints. Previous work Boujemaa et al. (2024) considered circularity under an infinite horizon but ignored stock and customer limits. We propose a finite-horizon dynamic programming framework in which prescriptive replacement decisions account for circularity, while customer and availability constraints are modeled through time-varying costs. The behavior of the resulting op-

timal maintenance policy, derived from the dynamic programming optimization, is then tested through simulations. The paper is organized as follows: Section 2 reviews relevant literature, Section 3 and 4 present the proposed methodology of the optimization process including different types of constraints and associated results.

2. Literature Review

Recent research in predictive maintenance and remanufacturing has advanced the integration of sustainability into operational decision making. de Jesus Santos et al. (2023) review maintenance policies incorporating reuse and remanufacturing, highlighting sustainability benefits and gaps in linking environmental and social aspects with practical constraints. Burggräf et al. (2022) propose adaptive remanufacturing models and life-cycle assessment frameworks for capital goods, focusing on extended component lifetimes and economically viable maintenance actions. However, these studies mainly address

strategic or tactical planning, with limited attention to operational scheduling and the integration of circularity into degradation-based models. Operational-level frameworks have emphasized data-driven scheduling and robustness under uncertainty, yet often overlook industrial constraints such as limited spare inventories or service requirements. Maintenance optimization literature has advanced finite-horizon and multi-component planning: Kivanç et al. (2024) develop scalable multi-objective optimization without considering reuse, Liu et al. (2021) examine finite-horizon condition-based maintenance for dependent degradation processes, and Pater and Mitici (2021) address limited spare stocks but without linking to circularity or sustainability. Overall, these studies indicate progress in promoting circularity and optimizing maintenance under realistic constraints, but no framework simultaneously integrates circularity, stock availability, and customer related operational limits within finite-horizon planning. This gap motivates the present approach, aiming to deliver maintenance decisions that are both sustainable and operationally feasible.

3. Maintenance Optimization Under Circularity And Spare Parts Availability Constraints

This section presents the methodology for optimizing maintenance decisions over a finite horizon under multiple operational constraints. The approach is built as follow: circularity is integrated into a condition-based maintenance model, then time-varying costs introduce availability and customer constraints. Each phase includes simulation results illustrating the behavior of the optimal policies.

3.1. Integration Of Circularity

3.1.1. Problem Formulation

This study focuses on a vehicle component inspired by the Diesel Particulate Filter (DPF), a critical and costly part that is commonly subject to remanufacturing. During the service contract, the system is periodically inspected, and maintenance decisions are based on the observed degradation.

At each decision epoch, the operator chooses between continuing operation or replacing the component with an original or a remanufactured part. Remanufactured components are cheaper but degrade faster, creating a cost–durability trade-off optimized over a finite horizon using dynamic programming. In this work, we adopt a Condition-Based Maintenance (CBM) strategy. CBM is a dynamic maintenance approach in which maintenance decisions are based on the actual condition of the component rather than on fixed time intervals. Maintenance actions are triggered according to the observed degradation level, allowing unnecessary replacements to be avoided while reducing the risk of unexpected failures. We denote the degradation level of a component at time t by $X(t)$, where $t \in \mathbb{R}^+$. For an original component, the degradation level at the time of installation (i.e., $t = 0$) and after each replacement is assumed to be zero. Remanufactured components are also assumed to be installed with an initial degradation level equal to zero, i.e., $x_{\text{reman}} = 0$. The degradation evolution follows a stochastic process with independent, non-negative, and stationary increments, and the component fails when the degradation $X(t)$ reaches a threshold L . It is modeled using a Gamma process, suitable for cumulative deterioration, with shape and scale parameters $(\alpha_{\text{original}}, \beta_{\text{original}})$ for original components and $(\alpha_{\text{reman}}, \beta_{\text{reman}})$ for remanufactured ones. The continuous degradation process is discretized into a discrete-time Markov chain with stationary and memoryless degradation increments. This discretization, inspired by the framework proposed by de Jonge (2019), allows the degradation trajectory to be represented by a finite number of discrete states, each corresponding to a specific level of wear.

3.1.2. Dynamic Programming Approach

Dynamic programming (DP) recursively solves finite-horizon decision problems by working backward from the final time step. At each time step t and system state S , the value function $V_t(S)$ evaluates all possible actions and selects the one minimizing the total cost. Optimal actions are stored in a policy matrix, defining the strategy for

each decision epoch. In our case study, the system state S at each time step $t \in \{0, 1, \dots, T\}$ is defined as a tuple $S = (x, r)$, where $x \in \{0, 1, \dots, L\}$ denotes the current degradation level of the component and $r \in \{0, 1\}$ indicates whether the installed component is remanufactured ($r = 0$) or original ($r = 1$). At each decision epoch, the possible actions $a \in A(x)$ are:

- $a = 0$: No replacement
- $a = 1$: Replacement with Remanufactured part
- $a = 2$: As good as new replacement

However, for degraded states where $x = L$, the system is considered failed and must be replaced with an original component. Thus, in this case, the only admissible action is $a = 2$, regardless of r . The optimization problem consists in selecting, at each decision epoch t , the action $a \in A(x)$ that minimizes the expected cumulative maintenance cost until the end of the planning horizon. This is achieved by recursively computing the value function $V_t(x, r)$.

$$V_t(x, r) = \min_{a \in A(x)} V_t^a(x, r) \quad (1)$$

The value function $V_t(x, r)$ represents the minimum expected total maintenance cost from state (x, r) at time t until the end of the planning horizon, assuming optimal decisions are made. Here, $V_t^a(x, r)$ denotes the cost associated with action a at time t , including the immediate cost of the action and the expected future cost from the resulting next state. The term P^r denotes the transition probability matrix associated with the degradation dynamics of the component. Specifically, matrix P^r has $(L+1) \times (L+1)$ elements, where L is the number of discrete degradation states. The entry $P^r(i, j)$ represents the probability of transitioning from degradation level x_i to x_j over one time step, given that the component is of type r . When $r = 0$, the transition probabilities correspond to a remanufactured component, whereas $r = 1$ refers to an original component. The parameter $C_{\text{prev-reman}}$ denotes the preventive replacement cost associated with installing a remanufactured component, while $C_{\text{prev-new}}$ represents the preventive replacement cost of an original component. The corrective replacement cost, denoted by C_{corr} , is

incurred when the degradation level reaches the failure threshold and corresponds to a full system replacement. When the degradation level reaches $x = L$, the system is considered failed and corrective maintenance is mandatory. Together, these parameters characterize the maintenance decision process and enable the optimization of replacement policies under different degradation dynamics and cost structures.

The time increment between two decision epochs is denoted by τ .

The value associated with each admissible action is defined as follows. For $x \in \{0, \dots, L-1\}$, $r \in \{0, 1\}$

No replacement ($a = 0$):

$$V_t^0(x, r) = \sum_{y=x}^L P_{xy}^{(r)} V_{t+\tau}(y, r) \quad (2)$$

In this first case, since no replacement is performed, this action does not incur any immediate cost. The associated value function accounts only for the expected future cost (the effect), evaluated through the transition probabilities $P_{xy}^{(r)}$ between the current state and the possible states y at the next inspection.

Replacement with an original component ($a = 2$):

$$V_t^2(x, r) = \sum_{y=0}^L P_{0y}^{(1)} V_{t+\tau}(y, 1) + C_{\text{prev-new}} \quad (3)$$

In this case, the component is replaced by an original one, which restores the system to the initial state. An immediate replacement cost $C_{\text{prev-new}}$ is added. The future expected cost is then evaluated using the transition probabilities $P_{0y}^{(1)}$, which describe the evolution of the new component from state 0 to possible states y at the next inspection time, here $r=1$ because we are dealing with an original component.

Replacement with a remanufactured component ($a = 1$):

$$V_t^1(x, r) = \sum_{y=x_{\text{reman}}}^L P_{x_{\text{reman}},y}^{(0)} V_{t+\tau}(y, 0) + C_{\text{prev-reman}} \quad (4)$$

In this case, the failed component is replaced by a remanufactured one, which brings the system to the degradation state x_{reman} . Here we will work

with $x_{\text{reman}} = 0$. An immediate replacement cost $C_{\text{prev-reman}}$ is incurred. The future expected cost is then computed using the transition probabilities $P_{x_{\text{reman}},y}^{(0)}$, which describe the evolution of the remanufactured component from state x_{reman} to possible states y at the next inspection time, here $r=0$ as the component is remanufactured.

For $x = L$:

Corrective maintenance is mandatory and the only admissible action is replacement with an original component:

$$V_t^2(L, r) = \sum_{y=0}^L P_{0y}^{(1)} V_{t+\tau}(y, 1) + C_{\text{corr}} \quad (5)$$

The dynamic programming recursion is initialized using the following terminal condition:

$$V_T(x, r) = \begin{cases} 0, & x < L, \\ C_{\text{corr}}, & x = L. \end{cases} \quad (6)$$

3.1.3. Results

Once the dynamic programming recursion is solved, the optimal maintenance policy is obtained for each decision epoch t and system state (x, r) by selecting the admissible action that minimizes the value function. The resulting decisions are stored in time- and state-dependent policy matrices, differentiated by component type. These policies are then analyzed based on numerical results to assess whether threshold-based structures with respect to the degradation level emerge. For each time step, degradation thresholds beyond which component replacement becomes optimal are extracted, leading to two distinct thresholds corresponding to remanufactured and original components. Their evolution over the finite horizon is examined to assess the influence of remaining time and component condition on maintenance decisions, and to highlight the trade-off between cost savings and degradation dynamics induced by circularity. The figures below illustrate the evolution of the optimal replacement thresholds and Monte Carlo simulations of degradation trajectories under the optimal policy. The numerical results are obtained using a planning horizon of $T = 960$ time steps, an inspection interval $\tau = 4$, a maximum degradation level

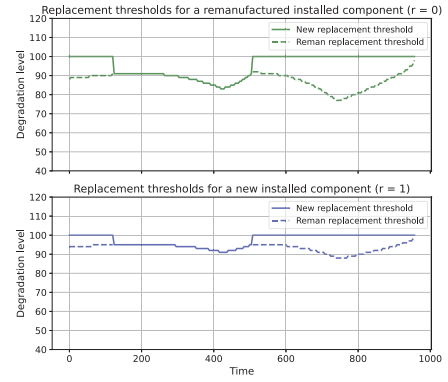


Fig. 1. Optimal replacement thresholds over time for remanufactured and original components

$L = 100$, and Gamma degradation models with parameters $(\alpha_{\text{original}}, \beta_{\text{original}}) = (0.5, 1.0)$ and $(\alpha_{\text{reman}}, \beta_{\text{reman}}) = (0.416, 2.0)$, chosen to represent realistic stochastic degradation behavior.

The value of T is chosen to be consistent with the average lifetimes of original and remanufactured components, which are approximately 200 and 120 time steps, respectively, thereby allowing multiple replacement cycles to be observed over the horizon.

The results illustrated in Fig. 1 and Fig. 2 indicate that the optimal replacement strategy follows a threshold policy. For replacements with an original or a remanufactured component, there is a level of degradation above which a replacement is carried out. This level corresponds to the replacement threshold at time t .

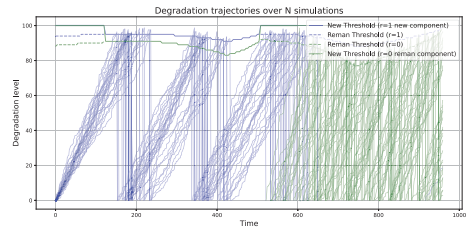


Fig. 2. Degradation trajectories over time under the optimal maintenance policy. Blue curves correspond to original components, while green curves represent remanufactured components

According to the graphs, the threshold is not constant throughout the T horizon (unlike the thresholds of policies optimized for an infinite horizon). the replacement threshold varies from one moment to another depending on the position in the T interval. During the first period of the contract, replacements are not particularly recommended because the system is new and functioning well. If there is ever a replacement, it will be remanufactured (original and remanufactured thresholds are rather high, but the remanufactured threshold is lower than the new threshold). Then, in the middle of the horizon, it is recommended to replace with original parts. This reflects the compromise with the useful life of the original parts, which is interesting given that there is still a good period remaining on the contract despite its higher cost, and we note that the behavior of the remanufactured threshold varies particularly as we approach the end of the horizon. This reflects a tendency not to replace with an original component but rather to favor cheaper remanufactured replacements because the contract will soon be over anyway. Towards the end of the horizon, replacement thresholds tend to increase so as not to recommend replacement, given that the contract has ended, thus avoiding additional costs.

3.2. Integration of Customer and Spare Parts Availability Constraints (Time varying Costs)

This section shows how time-varying costs representing stock availability and customer constraints affect optimal maintenance policies.

3.2.1. Spare Parts availability Constraints via Time Varying Costs

This subsection introduces spare parts availability constraints through time-varying preventive replacement costs, without modifying the structure of the dynamic programming model. Over the finite horizon T , a time interval $[T_1, T_2]$ is defined during which remanufactured components are assumed to be unavailable or difficult to access. This constraint is modeled by increasing the preventive replacement cost of remanufactured components during this period, while the standard previously used cost applies outside $[T_1, T_2]$. This approach preserves the option of remanufactured replacement at a higher cost, representing

backordering or delayed delivery, and allows the optimization framework to determine whether replacement with original component or postponement is preferable. As in Section 2, the system state is represented by (x, r) , and we have same possible actions to do, for $(a = 0)$ and $(a = 2)$ the equations of cost functions are the same since these decisions does not depend of stock availabilities of remanufactured components. Spare parts availability constraints are introduced by allowing the preventive replacement cost of remanufactured components to vary over time. Specifically, the cost associated with action $a = 1$ depends on the inspection time t , as follows:

$$V_t^1(x, r) = \begin{cases} \sum_{y=x_{\text{reman}}}^L P_{x_{\text{reman}}, y}^{(0)} V_{t+\tau}(y, 0) + C_{\text{prev-reman}}, & t \notin [T_1, T_2], \\ \sum_{y=x_{\text{reman}}}^L P_{x_{\text{reman}}, y}^{(0)} V_{t+\tau}(y, 0) + C_{\text{reman-indisp}}, & t \in [T_1, T_2]. \end{cases} \quad (7)$$

The parameter $C_{\text{reman-indisp}}$ denotes the increased replacement cost associated with remanufactured components during the unavailability period and satisfies $C_{\text{reman-indisp}} > C_{\text{prev-reman}}$. Failure and terminal conditions remain identical to those defined in the previous section.

3.2.2. Customer Constraints via Time Varying Costs

In addition to spare parts availability constraints, maintenance decisions are subject to customer-imposed limitations. Customers may define time periods during which maintenance operations are undesirable due to operational requirements, leading to additional penalties. These constraints are modeled by introducing a second time interval $[T_3, T_4] \subset [0, T]$, distinct from the availability interval $[T_1, T_2]$, during which the preventive replacement costs of both original and remanufactured components are increased. This results in time-varying replacement costs $C_{\text{prev-reman}}(t)$ and $C_{\text{prev-new}}(t)$, which are incorporated into the dynamic programming value functions. If replacement with an original component is performed ($a = 2$), the value function is updated as below where $C'_{\text{prev-new}}$ is the higher than $C_{\text{prev-new}}$ reflecting that the maintenance operation at this time interval is difficult to achieve. :

$$V_t^2(x, r) = \begin{cases} \sum_{y=0}^L P_{0y}^{(1)} V_{t+\tau}(y, 1) + C_{\text{prev-new}}, & x \in \{0, \dots, L-1\}, t \notin [T_3, T_4], \\ \sum_{y=0}^L P_{0y}^{(1)} V_{t+\tau}(y, 1) + C'_{\text{prev-new}}, & x \in \{0, \dots, L-1\}, t \in [T_3, T_4]. \end{cases} \quad (8)$$

For replacement with a remanufactured component ($a = 1$), the value function is:

$$V_t^1(x, r) = \begin{cases} \sum_{y=x_{\text{reman}}}^L P_{x_{\text{reman}}}^{(0)} V_{t+\tau}(y, 0) + C_{\text{prev-reman}}, & t \notin [T_1, T_2] \cup [T_3, T_4], \\ \sum_{y=x_{\text{reman}}}^L P_{x_{\text{reman}}}^{(0)} V_{t+\tau}(y, 0) + C_{\text{reman-indisp}}, & t \in [T_1, T_2], \\ \sum_{y=x_{\text{reman}}}^L P_{x_{\text{reman}}}^{(0)} V_{t+\tau}(y, 0) + C'_{\text{prev-reman}}, & t \in [T_3, T_4]. \end{cases} \quad (9)$$

Here, $C_{\text{prev-reman}}$ and $C_{\text{prev-new}}$ are the baseline preventive replacement costs, $C_{\text{reman-indisp}}$ accounts for the unavailability of remanufactured components during $[T_1, T_2]$, and $C'_{\text{prev-reman}}$ corresponds to the penalty due to customer constraints during $[T_3, T_4]$. This formulation integrates both component availability and customer constraints into the dynamic programming framework. The objective of this part is to examine the behavior of the optimal maintenance policy throughout the entire planning horizon T when both component availability and customer constraints are taken into account. The resulting policies and thresholds will be compared with the scenario where only the component availability constraint is applied. These analyses provide insight into how the additional customer-imposed limitations affect replacement decisions over time.

3.2.3. Results

We analyze the impact of component availability constraints on the optimal maintenance policy using Monte Carlo simulations to evaluate the optimal policy obtained based on the dynamic programming model with time-varying costs. The system is considered over a finite horizon of $T = 5$ years, with weekly inspections ($\tau = 4$). The degradation parameters are identical to those used previously, yielding average lifetimes of approximately 120 time units for remanufactured components and 200 for new components. The avail-

ability constraint is modeled by increasing the preventive replacement cost of remanufactured components over the interval $[T_1, T_2]$, with $T_1 = 700$ and $T_2 = 820$, chosen to be located near the end of the horizon where remanufactured replacements are typically more frequent, see Fig. 2. The cost parameters are set to $C_{\text{corr}} = 200$, $C_{\text{prev-new}} = 30$, $C_{\text{prev-reman}} = 20$ under normal conditions.

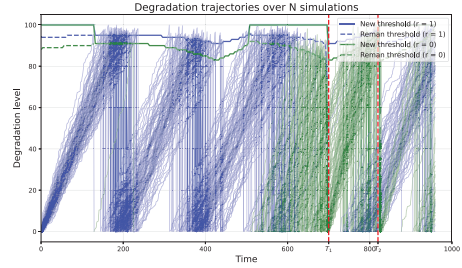


Fig. 3. Optimal policy and degradation trajectories with LIMITED availability of reman components

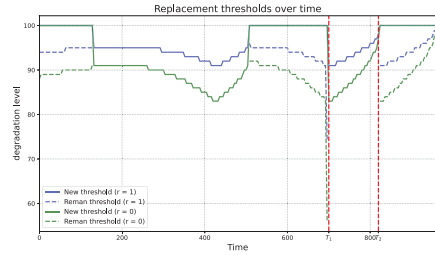


Fig. 4. Replacement thresholds with LIMITED availability of reman components

Fig. 3 illustrates the resulting replacement behavior. Approaching the end of the horizon starting from $t = 500$ up to time T_1 , most replacements are performed using remanufactured components, as expected given their lower cost. During the interval $[700, 820]$, the temporary cost of remanufactured components is increased to 60, which is twice the cost of a new component. As a consequence, the optimal policy entirely switches to replacement with new components that are available and cost less than remanufactured components. After time T_2 , some remanufactured replacements progressively reappear, indicating that the policy waits for the end of the

unavailability period to reintroduce the less expensive option. Fig. 4 shows that the remanufactured components replacement thresholds fall just before the start of the period of unavailability of replacement components, which highlights the anticipation of unavailability. Then, during this period, only original replacements are possible to perform and associated thresholds increase as time goes on. Then, just after this period, starting in T_2 , original replacement threshold increases up to L discouraging original replacements and the remanufactured replacement threshold drops again because it becomes more cost-effective to replace with remanufactured components, since we are no longer in the period of unavailability. It then increases as we approach the end of the contract in order to discourage replacements at the end of the contract. Overall, the optimal policy effectively balances cost and availability by anticipating the period of temporary unavailability of remanufactured components and performing remanufactured replacements just before this period. This strategy avoids costly or impossible replacements during the constraint interval, while switching back to remanufactured components as soon as the temporary constraint is lifted, thus ensuring continuity of operations at a reduced overall cost. It should be noted that, in this experiment, the penalty cost associated with remanufactured unavailability is deliberately chosen to be higher than the cost of a new component, in order to clearly highlight the impact of the availability constraint on the maintenance decisions.

To further highlight the behavior of the optimal policy under cost variations due to component unavailability, we extend the period of remanufactured component unavailability to cover the entire interval during which remanufactured replacements are typically required, we set $T_1 = 700$ and $T_2 = T$. This allows us to observe how the optimal policy adapts when the less expensive option is unavailable throughout the period of high demand, providing additional insight into the system's anticipative behavior. When we extend the period of unavailability of remanufactured components until the end of the horizon in Fig. 5, remanufactured replacements that were not

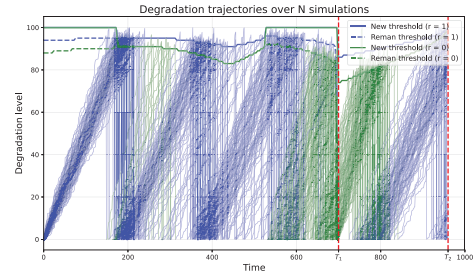


Fig. 5. Optimal replacement thresholds and simulated degradations with LIMITED availability of reman components during high demand period

there when we optimized without this constraint appear at the beginning of the horizon (around $t = 150$). In addition, before the $[T_1, T_2]$ interval, remanufactured replacements are made to anticipate unavailability. This is confirmed by the drop in the remanufactured threshold just before T_1 , then throughout the $[T_1, T_2]$ interval. The original replacement threshold decreases because, given the unavailability of remanufactured parts, only original replacements are possible, then towards the end, as we approach T , the thresholds increase so as not to replace at the end, just as in the previous cases. In conclusion, the policy takes into account the constraint of unavailability of remanufactured components by adapting decisions in the first part of the horizon to compensate for the new replacements that will be made during $[T_1, T_2]$. The introduction of customer constraints, represented by the interval $[T_3, T_4]$ such that $T_3 = 600$ and $T_4 = 650$, further emphasizes the anticipative behavior of the optimal policy. These numerical values are chosen to position the constraint in a time region where replacement actions are already likely to occur, and prior to the remanufacturing stock constraint interval $[T_1, T_2]$, thereby allowing us to analyze how the policy anticipates and coordinates multiple interacting constraints over the planning horizon. The graphs in Fig. 6 and Fig. 7 indicate that just before the customer constraint period, the remanufacturing threshold is lowered to allow preventive replacements. During the constraint period, no planned replacements occur, although a few corrective replacements are observed in simulations (50 out of 500 runs). After this

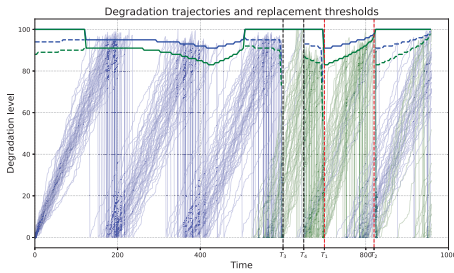


Fig. 6. Trajectories of degradation under component availability and customer constraints

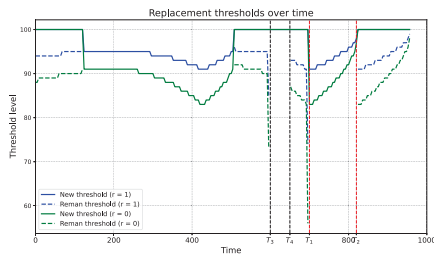


Fig. 7. Replacement thresholds of the optimal policy under spare parts availability and customer constraints

period, and before the temporary unavailability of remanufactured spare parts, the reman threshold again decreases to anticipate potential stock shortages. For the remainder of the horizon, the policy behaves in the same way as it did prior to the integration of the customer constraint.

4. Conclusion and perspectives

This work addressed the optimization of prescriptive maintenance decisions over a finite horizon, explicitly integrating circularity, component availability, and customer-related constraints. The proposed framework demonstrates how maintenance policies can strategically schedule preventive replacements to anticipate periods of high cost or limited component stock, while adapting to the uncertainty of component degradation and temporary operational constraints. Future work could extend the model by integrating spare parts availability as a state in a four-state dynamic programming loop, allowing maintenance decisions to explicitly account for stock levels. Additional perspectives include sensitivity analysis of degradation param-

eters and costs, and extension to multi-component systems for optimized, sustainable maintenance.

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