Journal of Data Analytics and Intelligent Decision-making Vol. 1 Issue. 2 (2025) 1-12

Journal of Data Analytics and Intelligent Decision-making

Journal homepage: jdaid.qom.ac.ir

University of Qom

A New Approach to Improve System Reliability by Eliminating Early Failures

Hadi Gholinezhad*[a], Ramezan Khosravi[b]

a. Assistant Professor, Department of Industrial Engineering, University of Gonabad.
b. Assistant Professor, Department of Industrial Engineering, University of Gonabad.

ARTICLEINFO

Keywords:
Reliability
Time-dependent failure rate
Bathtub curve
Erlang distribution

ABSTRACT

One of the key criteria for assessing the durability of a system is evaluating the probability of its performance over a specified time period, which is refered to as reliability. This probability depends on the performance of the system's components, and the failure rate of each component impacts this issue significantly. In most related studies, it is assumed that the failure rates of components remain constant over time; however, this rate is often not constant due to various factors. A common pattern for changes in failure rates over time is known as the bathtub curve, where the failure rate is initially high, decreases over a period, and then eventually increases again. The early life period, during which the failure rate of components is initially high and then decreases, can lead to early failures and a reduction in the probability of component performance. By conducting controlled experiments before the practical use of a system, this initial period can be eliminated, thereby preventing early failures, which in turn can lead to improved system reliability. This paper examines the impact of eliminating the early life period on system reliability. The results indicate that the elimination of this period does not necessarily lead to improved reliability under all conditions, as it depends on specific parameters. This paper will analyze the sensitivity of these parameters and the conditions under which eliminating the early life period can improve reliability.

1. Introduction

One of the key factors in measuring the quality of any system is its reliability. It refers to the probability of the system performing correctly over a specified time period, and there has always been an effort to improve it. One of the factors influencing system reliability is how the components of the system are combined and positioned together. There are various methods for

* Corresponding author.
E-mail addresses: gholinezhad.hadi@gonabad.ac.ir (H. Gholinezhad), khosravi87@gmail.com (R. Khosravi)
Received 19 May 2025; Received in revised form 21 June 2025; Accepted 30 July 2025
Available online 30 August 2025

Cite this article: Gholinezhad, H., Khosravi, R. (2025). A New Approach to Improve System Reliability by Eliminating Early Failures .*Journal of Data Analytics and Intelligent Decision-making*, 1(2), 1-12.
https://doi.org/10.22091/jdaid.2025.14317.1011

combining the components of a system, including series, parallel, and series-parallel combinations. In all these combinations, the overall reliability of the system depends on the reliability of its components. Although the reliability of each system depends on its configuration, in all systems, the reliability of the system is contingent upon the reliability of its components. As the reliability of the components increases, the overall reliability of the system also increases.

The reliability of each component in a system depends on its failure rate. Clearly, the higher the failure rate of a component, the lower the probability of failure and, consequently, its reliability. Two main factors that can lead to the failure of system components are wear (Fang et al., 2020; Hu et al., 2022; Li et al., 2023; Zhang et al., 2024) and shock (Gong et al., 2020; Peng & You, 2021; Poursaeed, 2021; Wang et al., 2020; Zhao et al., 2021). Wear may result from factors such as corrosion, abrasion, rust, temperature fluctuations, and cracking. On the other hand, shocks including physical, electrical, and thermal shocks can lead to component failures. Typically, electronic components are more susceptible to failure due to shocks, while mechanical components suffer damage due to wear. In some cases, these two factors can simultaneously lead to the failure of a component (Bian et al., 2021; Dong et al., 2021; Huang et al., 2021; Liu et al., 2021; Mousavi et al., 2025; Sun et al., 2021). Overall, various conditions and factors determine the failure or breakdown rate of components. In most studies conducted in this field, the failure rate of components has been assumed to be constant (Attar et al., 2023; Hsieh et al., 2021; Reihaneh et al., 2022; Sadeghi et al., 2021; Yeh et al., 2022). However, in reality, the failure rate of components is not usually constant; it tends to increases over time with repeated use of a system (Abunima & Teh, 2020; Fan et al., 2023; Sharifi et al., 2023; Zhang et al., 2024; Zio & Gholinezhad, 2023). Therefore, the assumption of a constant failure rate over time can lead to serious errors in assessing system reliability. These incorrect assumptions can also result in non-optimal outcomes and waste of resources, including costs and time, in optimization issues.

Two common methods for improving system reliability include using backup components alongwith the main system components and using components with higher reliability. Using backup components means placing additional components as spares alongside the system's components, which can be utilized in case of failures of the system components to prevent system breakdown. Using components with higher reliability involves employing higher quality components with a lower failure rate that experience failures over a longer period. This approach increases the likelihood of their functioning within a specified timeframe, thereby enhancing both their reliability and the overall reliability of the system. Both methods require additional costs and resources, thereby increasing the system's overall costs and resources, such as weight and volume.

In this paper, a new approach to increasing system reliability is presented, which has not been addressed in prior research. As mentioned, under real conditions, the failure rate of a system's components is generally not constant and changes over time. One common model for describing these changes is the bathtub curve, illustrated in Figure 1. This model divides the lifespan of each component into three stages: the early life period, the useful life period, and the wear-out period. In the first stage, known as the infant mortality or early failure period, the failure rate is initially high and decreases over time. During this period, components require adjustments and rectification of initial defects and must adapt to their surrounding environment. Over time, as initial defects are resolved, the compatibility of components increases, and they reach their optimal state. During this relatively short phase, the likelihood of failure and malfunction gradually decreases as the components operate. After the initial defects and faults are resolved, the failure rate remains relatively constant in the second stage and does not change. This stage, known as the useful life of the components, is characterized by random failures. In the third stage, after surpassing the normal lifespan, components enter the wear-out or wear-out phase. During this stage, the failure rate continuously increases, indicating the wear and wear-out of the components.

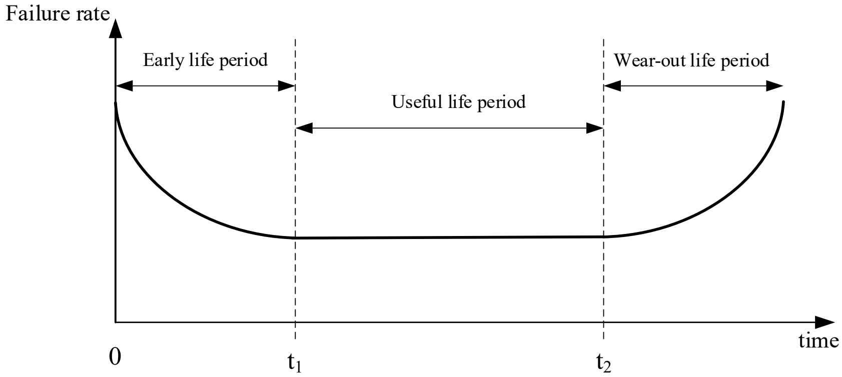


Figure 1. Bathtub Curve for Time-Dependent Failure Rate

In Figure 1, the trend of the useful life of a component indicates that during this period, the failure rate is minimized and the probability of failure decreases. Conversely, during the early life stages and the wear-our period, the failure rate is high, and consequently, the probability of failure also increases. Therefore, to enhance reliability, it is essential to ensure that components enter the useful life phase as quickly as possible and remain in this stage for as long as possible. The wear-out period, which is caused by the use and wear of the component, is unavoidable. Although it can be delayed using specific methods, these methods depend on environmental conditions and how the component is used; if these conditions remain constant, the start time of the wear-out period will be approximately fixed. During the wear-out life, as time progresses, preventive maintenance, major repairs, and sometimes, replacement of components with new ones are suggested. Regarding the early life period, if part or all of the early life can be eliminated using techniques such as pre-use testing or initial use of components, it can significantly improve the reliability of both the components and the system. This paper examines the impact of eliminating the early life period on the reliability of components and systems in more detail.

2. Modeling and Formulation

In this section, a mathematical model of system reliability is examined and presented, where the failure rates of components are time-dependent and follow a bathtub curve, addressing the impact of eliminating the early life period of the system. The following assumptions are considered for the proposed model:

- The system and its components are binary, existing in either a completely functional or failed state.
- The components of the system are non-repairable, and no preventive maintenance is applied.
- The lifespan of the system components follows an Erlang distribution with a time-dependent rate parameter $\lambda(t)$. Other characteristics of the components are fixed and deterministic.

To examine the mentioned model, the following symbols are used:

- $r(t)$: Reliability of a component at time t
- $f(t)$: Probability density function of a component at time t
- λ, k: Parameters of the Erlang distribution with the assumption of a constant rate parameter
- $\lambda(t)$: Time-dependent rate parameter for the Erlang distribution at time t
- λ_{a-b}: Mean rate parameter between time a and b

If the lifespan of a component follows an Erlang distribution with constant parameters k and λ, its failure occurs due to shocks at a rate of λ, and the component fails upon the occurrence of k shocks. Therefore, the probability of the component remaining functional at time t, or its reliability at time t, is equal to the probability that fewer than k shocks occur by time t. Consequently, the reliability of the component at time t is given by relation (1).

$$r(t) = \int_t^{\infty} f(t)dt = \sum_{j=0}^{k-1} \frac{e^{-\lambda t}(\lambda t)^j}{j!} \tag{1}$$

If the rate parameter of the Erlang distribution is time-dependent and represented as $\lambda(t)$, shocks occur at a time-dependent rate according to a Poisson process. In a non-homogeneous Poisson process with rate $\lambda(t)$, the probability of j shocks occurring between time a and b is given by relation (2).

$$P\{N(b) - N(a) = j\} = \frac{e^{-\lambda_{a-b}}(\lambda_{a-b})^j}{j!} \tag{2}$$

In this relation, $N(t)$ represents the number of shocks that have occurred according to the non-homogeneous Poisson process by time t, and λ_{a-b} is calculated according to relation (3).

$$\lambda_{a-b} = \int_a^b \lambda(t)dt \tag{3}$$

In this case, the reliability of a component whose lifespan follows an Erlang distribution with a time-dependent rate parameter $\lambda(t)$ is obtained from relation (4).

$$r(t) = P\{N(t) - N(0) < k\} = \sum_{j=0}^{k-1} \frac{e^{-\lambda_{0-t}}(\lambda_{0-t})^j}{j!} = \sum_{j=0}^{k-1} \frac{e^{-\int_0^t \lambda(u)du}(\int_0^t \lambda(u)du)^j}{j!} \tag{4}$$

In this paper, the failure rate is considered as a bathtub curve, as shown in Figure 1. To this end, the function $\lambda(t)$ must be characterized such that it is initially decreasing, then constant, and finally increasing. In this paper, the function $\lambda(t)$ is considered as a piecewise function according to relation (5), where t_1 is the end time of the early life period and the start of the useful life period, and t_2 signifies the end time of the useful life period and the start of the wear-out period. The parameters a, b, α, and β are constant values, and λ_c is the constant failure rate during the useful life period.

$$\lambda(t)=\begin{cases} at^{\alpha} & ; \quad 0 \le t \le t_1 \\ \lambda_c & ; \quad t_1 < t < t_2 \\ bt^{\beta} & ; \quad t \ge t_2 \end{cases} \tag{5}$$

For the function $\lambda(t)$ in relation (5) to be decreasing during the early life period and increasing during the wear-out period, α and β must be negative and positive numbers, respectively. Additionally, the values of a and b must be determined so that the above function is continuous at points t_1 and t_2. Therefore, after calculating the values of a and b, relation (5) can be expressed as relation (6).

$$\lambda(t)=\begin{cases} \lambda_c(\frac{t}{t_1})^{\alpha} & ; \quad 0 \le t \le t_1 \\ \lambda_c & ; \quad t_1 < t < t_2 \\ \lambda_c(\frac{t}{t_2})^{\beta} & ; \quad t \ge t_2 \end{cases} \tag{6}$$

It is worth noting that other relations can also be used for the early life and wear-out periods. However, it is necessary to ensure their decreasing nature during the early life period and increasing nature during the wear-out period, as well as the continuity of the function $\lambda(t)$ at points t_1 and t_2.

The new approach proposed in this paper involves eliminating the early life period through testing or initial use in a controlled environment before the practical use of the system. It is assumed that by removing the early life period, the length of the useful life does not change, and in fact, the bathtub curve, shown in Figure 1, shifts to the left by the length of the early life period. The result of removing the early life period for components is illustrated in Figure 2.

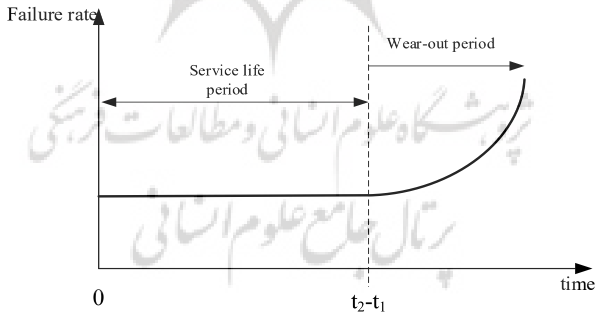


Figure 2. Failure Rate of Components After Eliminating the Early Life Period from the Bathtub Curve

As previously mentioned, during the early life period, the failure rate is initially, but decreases subsequently to a constant value, which is the failure rate during the useful life. Therefore, eliminating the early life period for a component reduces its failure rate at the start of operation and consequently increases its reliability. However, it is essential to note that removing the early life period will cause the wear-out period to begin earlier. As a result, it is expected that after a certain point, if the early life period is eliminated, the failure rate will experience higher values, and reliability will decrease more significantly. Therefore, it is crucial to determine whether the removal of the early life period improves or worsens reliability, considering the values of the effective parameters and the time at which we want to evaluate reliability. To clarify these aspects, a numerical example along with a sensitivity analysis of the mentioned parameters will be presented in the following sections.

3. Numerical Example

To analyze the impact of eliminating the early life period on the reliability of components and the system, an example is presented. This example involves a system composed of six components, where the lifespan of all components follows an Erlang distribution with a time-dependent rate parameter, in accordance with Figure 1 and relation (6). To determine the lifespan distribution of the components, it is necessary to specify the values of the effective parameters for each component. The relevant information regarding these parameters is provided in Table 1. Based on the data available in Table 1, the reliability of the components at mission time t=100 is calculated before and after the removal of the early life period, and the results are presented in Table 2.

Table 1. Numerical Example Data

Component Number	k	λ_c	α	β	t_1	t_2
1	6	0.052	-0.7	2	10	90
2	4	0.017	-0.5	1	15	120
3	5	0.043	-0.6	3	8	110
4	4	0.026	-0.6	2	12	80
5	3	0.023	-0.4	4	6	70
6	3	0.011	-0.3	6	9	95

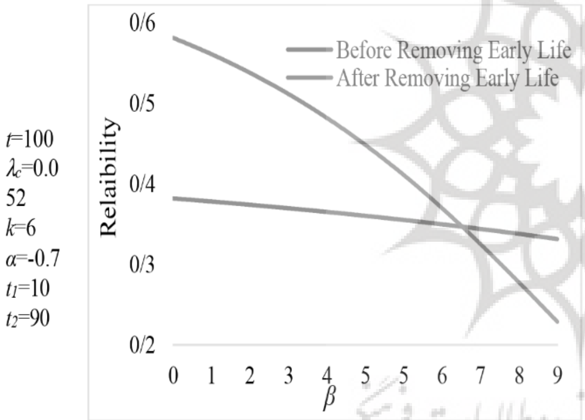
Table 2. Reliability of Numerical Example Components

Component Number	**Reliability (Before Removng Early Life)**	**Reliability (After Removing Early Life)**
1	0.5760	0.7153
2	0.8652	0.9068
3	0.6880	0.7626
4	0.7378	0.7649
5	0.7895	0.7106
6	0.8670	0.8552

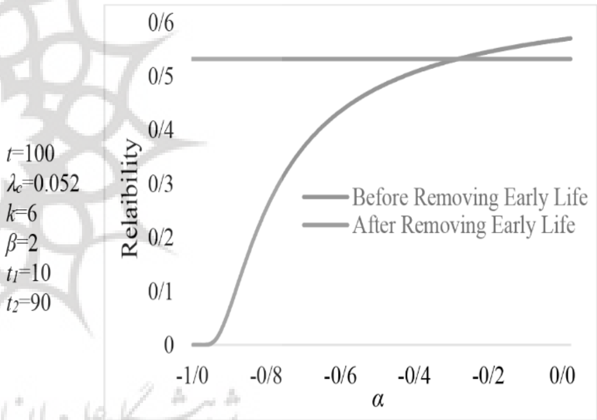
Based on the results obtained, the removal of the early life period has varying effects on the reliability of components; specifically, it increases reliability for the first four components while decreasing it for the last two components. This indicates that the removal of the early life period cannot be considered a definitive solution for improving reliability across all components. The changes in reliability resulting from the removal of this period are influenced by various parameters, such as α (which affects the slope of the failure rate decrease during the early life), β (which affects the slope of the failure rate increase during the wear-out period), t_1 (the end time of the early life period and the start of the useful life), t_2 (the end time of the useful life and the start of the wear-out period), t (the mission time at which reliability is evaluated), and λ_c (the constant failure rate during the useful life). For instance, if the removal of the early life period does not cause the start of the wear-out period to occur before the mission time, then the reliability will certainly improve due to the decreasing or constant failure rate over time. However, in other scenarios, the removal of the early life period may lead to a deterioration in reliability or no change at all. To evaluate the various potential outcomes, a sensitivity analysis of the reliability of one of the system components with respect to the mentioned parameters will be conducted.

4. Sensitivity Analysis

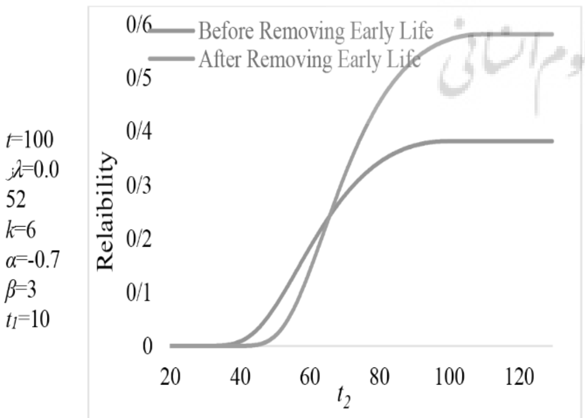
To analyze the trend of changes in reliability concerning variations in the mentioned parameters and to examine the impact of removing the early life period, the data related to the first component of the example presented in the previous section will be analyzed. For this purpose, one of the mentioned parameters (including α_1, α_2, t_1, t_2, t, and λ_c) will be selected each time, and assuming the other parameters remain constant, the trend of changes in reliability for different values of the selected parameter will be evaluated and presented. The results of this analysis and the trend of reliability changes for various parameter values are illustrated in Figure 3.



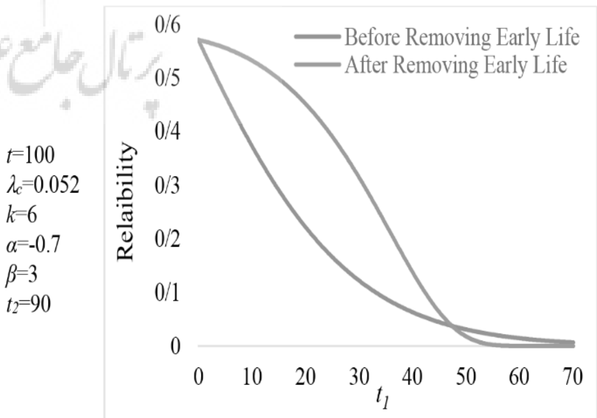
Reliable changes for different values β



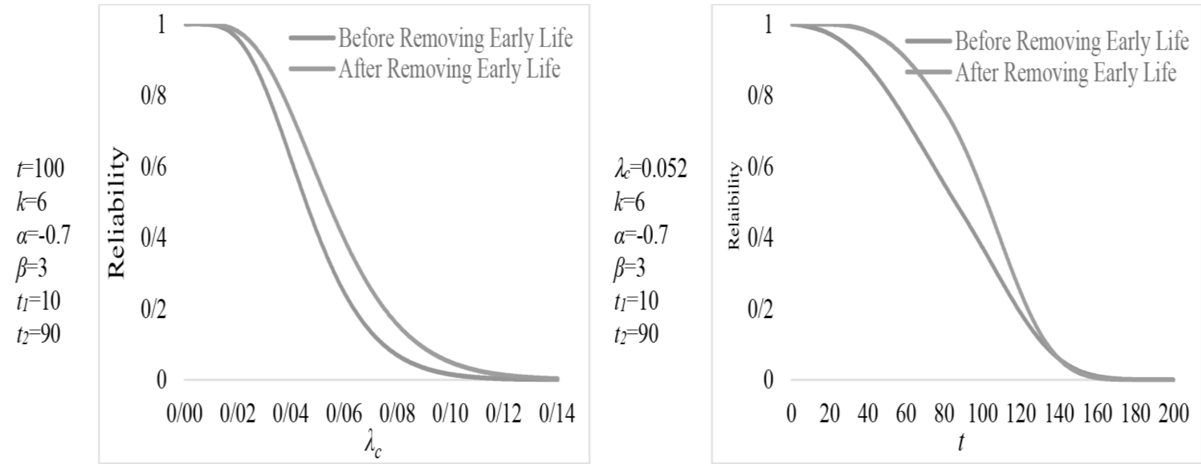
Reliable changes for different values α



Reliable changes for different values t_2



Reliable changes for different values t_1



Reliable changes for different values λ_c Reliable changes for different values t

Figure 3. Trend of Changes in the Reliability of the First Component for Different Values of the Effective Parameters

The results presented in section A of Figure 3 indicate that changing the value of α does not affect the reliability of the component after the removal of the early life period. This is because the removal of the early life period implies the absence of the initial decreasing failure rate. This implies that the initial decreasing failure rate does not influence α as a significant factor in the slope of the decreasing failure rate. Regarding the reliability of the component before the removal of the early life period, the results demonstrate an increasing trend for different values of α. As the value of α increases, the slope of the decreasing failure rate also increases (indicating a sharper reduction in the failure rate), which reduces the probability of failure during this period, thereby increasing reliability. It is also observed that for values of α less than approximately -0.3, the removal of the early life period improves reliability, while for higher values, this removal leads to a decrease in reliability.

According to the results shown in section B of Figure 3, the trend of reliability changes for different values of β indicates that for lower values of β, the removal of the early life period creates a more significant improvement in reliability. As the value of β increases, this improvement diminishes, such that for higher values of β, the removal of the early life period worsens reliability. It is observed that for values less than approximately 6.8, the removal of the early life period aids in improving reliability, while for values above 6.8, the opposite occurs. This phenomenon arises because the removal of the early life period accelerates the onset of the wear-out period, and an increase in β (as a significant factor in the slope of the increasing failure rate during the wear-out period) means a steeper slope of the failure rate increase in the wear-out period. Consequently, an increase in β results in a sharper rise in the failure rate, ultimately increasing the probability of failure and reducing reliability.

Analysis of the results from section C of Figure 3 highlights that for values of t_1 less than approximately 47, the removal of the early life period enhances reliability, while for higher values, this removal has a negative effect. Although increasing t_1 raises the probability of failure during the early life period, assuming t_2 remains constant, increasing t_1 leads to a reduction in the length of the useful life, thereby accelerating the onset of the wear-out period and ultimately decreasing reliability.

As observed in section D of Figure 3, the removal of the early life period decreases reliability for lower values of t_2, while for higher values, it has a positive effect. A low value of t_2 signifies that the wear-out period arrives sooner, and the removal of the early life period causes this period to start much earlier, consequently increasing the failure rate and the probability of failure. Conversely, a high value of t_2 means a later onset of the wear-out period.

Even with the removal of the early life period, the mission time occurs before the onset of wear-out, ultimately resulting in improved reliability due to the elimination of the high failure rate associated with the early life period.

The trend of reliability changes for various mission times t shown in section E of Figure 3 indicates that for lower values of t (less than approximately 140), the removal of the early life period increases reliability, while for higher values, it has the opposite effect, although the difference is minimal since the reliability approaches zero in both cases. This occurs because for lower values of t (the mission time when reliability is assessed), even with the removal of the early life period, the mission time occurs before the wear-out period begins, and the removal of the early life period, by eliminating the associated high failure rate, reduces the probability of failure and improves reliability. In contrast, for higher values of t, the removal of the early life period accelerates the onset of the wear-out period, increasing the likelihood of high failure rates during that period, thereby reducing reliability.

Finally, the analysis of reliability changes for different values of λ_c presented in section F of Figure 3 reveals that for all values of λ_c, the removal of the early life period will improve reliability. This is because changes in the value of λ_c affect the failure rate in all three lifespan periods. If the removal of the early life period improves reliability for a specific value of λ_c, this positive effect will also hold for other values of λ_c. It should be noted that if for another component with different specifications than those considered here, the removal of the early life period reduces reliability for a specific value of λ_c, this reduction will also occur for other values of λ_c.

Overall, based on the sensitivity analysis conducted for various parameters affecting the reliability of a component and the results obtained, it can be concluded that accurately determining all input parameter values is essential for evaluating the impact of removing the early life period on reliability. Therefore, it is not possible to provide a general rule for this topic, and one cannot expect improved overall system reliability simply by removing the early life period for all components. However, after accurately assessing the specifications of each component and evaluating their conditions individually, informed decisions can be made to remove the early life period for components where this action enhances their reliability, thereby improving the overall system reliability.

It is also important to mention that conducting tests and replacing damaged components during this process incurs significant time and costs. Nevertheless, this action can lead to increased system reliability and reduced failure probabilities, ultimately minimizing related costs. Therefore, the final decision regarding the removal of the early life period should be based on thorough economic analyses and will fall under the responsibility of relevant managers and decision-makers.

5. Conclusion and Recommendations

In this paper, a new approach was presented to improve the reliability of systems. This was achieved by assuming that the lifespan of the components of a system consists of three phases: the early life period, the useful life period, and the wear-out period. The impact of eliminating the early life period on their reliability was examined. To demonstrate this impact, the reliability of various components with different specifications and conditions was evaluated and analyzed in two scenarios: before and after the removal of the early life period.

The results indicated that in numerous cases, the removal of the early life period leads to improved reliability of components, while in some situations, it results in deterioration. Therefore, it cannot be generally stated that the removal of the early life period of a component will always improve or worsen its reliability; the outcome depends on various parameters, and different values of these parameters can yield different results.

To determine the effect of removing the early life period for a component, it is essential to accurately estimate and specify all influencing parameters. After determining these parameters and evaluating the conditions of each component, along with assessing their reliability before and after the removal of the early life period, informed decisions can be made. For components where the removal of the early life period improves reliability, this approach can enhance overall system reliability through controlled testing or initial use.

It is important to note that examining the conditions and specifications of components, conducting tests, and replacing damaged parts during these trials incurs significant costs. Therefore, the final decision regarding the implementation of the proposed approach may require economic evaluations and a comparison of the associated costs with costs such as system failures. This analysis will help determine whether the improvement in reliability justifies the expenses involved.

For future research in this area, it is suggested to consider alternative forms for the failure rate, explore other probability distributions for the lifespan of components, and conduct economic evaluations for the removal of the early life period.

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