Modifying the Extended Neyman's Smooth Test for Application in Accelerated Failure Time Models

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ABSTRACT

Accelerated life testing (ALT) is crucial for evaluating high-reliability units, requiring effective goodness-of-fit (GOF) techniques to test the underlying lifetime distribution across multiple stress levels. However, challenges arise due to the need to combine failure times from different stress levels to assess the adequacy of a lifetime distribution. This paper introduces a modified version of Neyman's smooth test, called the adapted extended Neyman's smooth test (AENST), to address these challenges within the accelerated failure time (AFT) model framework. The AENST is designed to test both Weibull and exponential distributions under constant stress with complete sampling. To evaluate its performance, the AENST is compared with the conditional probability integral transformation test (CPITT) using a simulation study. The results indicate that the AENST outperforms the CPITT in terms of power, making it a recommended tool for testing AFT models. A real dataset is also provided to demonstrate the application of the AENST.

1. Introduction

This chapter introduces accelerated life testing (ALT) and how such units help in extremely reliable conditions. However, an appropriate goodness of fit (GOF) technique is required to be developed for underlining lifetime distributions over different levels of stress. The core research question explores the effectiveness of the adapted extended Neyman's smooth test (AENST) in validating distributional assumptions of accelerated failure time (AFT) models under constant stress and complete sampling. Five sub-research questions are presented; these are if AENST can work for different levels of stress, comparing its performance against the conditional probability integral transformation test (CPITT), AENST's performance in Weibull distribution application, its ability in exponential distribution application, and the efficacy on real data examples. This paper will apply the quantitative methodology because the AENST will act as an independent variable and dependent variables as their validation outcomes. The article progresses from a literature review to methodology, results, and concludes with the implications of using AENST in AFT models.

2. Literature Review

This section reviews the existing research on GOF techniques in ALT, arranged according to the sub-research questions: multiple stress levels, comparison with CPITT, Weibull distribution, exponential distribution, and real data examples. Each section discusses the prior research, along with the hypothesis statement, where gaps that this paper is going to fill are underlined. Notable omissions include minimal consideration given to the integration of stress levels, fewer comparative studies, and a lack of verification for applying these techniques in real-world examples.

2.1 Handling Multiple Stress Levels in GOF Techniques

Early work on GOF techniques in ALT involved single stress levels, without good methods for how to combine failure times over several levels. The subsequent research had methods for integrating stress levels but suffered from losing precision. Current advances have better methods for stress integration but do not scale well. Hypothesis 1: AENST can efficiently combine failure times over multiple stress levels in ALT.

2.2 Comparison with Conditional Probability Integral Transformation Test

Early comparisons between various GOF tests often highlighted their relative strengths and weaknesses without detailed analyses. Mid-term studies began to focus on specific test comparisons, such as with CPITT, but often lacked a comprehensive evaluation framework. Recent research has improved comparative analyses but still leaves gaps in understanding specific contexts. Hypothesis 2: AENST outperforms CPITT in validating AFT models.

2.3 Application to Weibull Distribution

Initial applications of GOF tests to Weibull distribution often lack robustness against different parameter sets. Mid-term studies with more improved methodologies suffered from lack of consistency between various scenarios. Current developments have gone a step further in achieving more robustness but still limited for comprehensive applications. Hypothesis 3: AENST offers robust validations for Weibull distributions within AFT models**.**

2.4 Application to Exponential Distribution

Early studies applying GOF tests to exponential distribution often focused on theoretical frameworks without practical validation. Mid-term research included practical applications but faced challenges in model accuracy. Recent efforts have improved accuracy but require further practical validations. Hypothesis 4: AENST effectively validates exponential distributions in AFT models.

2.5 Real Data Scenarios

Initial studies for real data application of GOF tests were relatively less practical insight and more into theoretical. Intermediate studies started real data applications with a lack of complete analysis in most cases. Recent studies, though improved to some extent from real data applications, still needed broader validation. Hypothesis 5: AENST is effective for real-world applications of AFT models.

3. Method

This section outlines the quantitative research methodology applied to test the hypotheses proposed. It details the data collection and variable selection processes, providing a clear framework for evaluating the effectiveness of AENST in AFT models.

3.1 Data

Data are collected through a simulation study and real-world datasets, focusing on failure times across multiple stress levels in ALT. The collection method includes complete sampling under constant stress, with criteria ensuring the inclusion of diverse scenarios to test AENST's applicability to Weibull and exponential distributions.

3.2 Variables

Independent: AENST, Dependent: For Weibull and exponential distribution, validation outcomes: The control variables involved stress level variances and sampling conditions; it referenced literature to validate the reliability of the measurement method that records these variables for robustness in the analysis.

4. Results

This section presents the findings from the data analysis, which validate the hypotheses through statistical evidence. It begins with a descriptive statistical analysis of the collected data and progresses to regression analyses confirming the effectiveness of AENST in various contexts.

4.1 AENST's Effectiveness in Handling Multiple Stress Levels

This finding validates Hypothesis 1, demonstrating AENST's capacity to integrate failure times across multiple stress levels in ALT. Utilizing simulation data, the analysis shows that AENST maintains accuracy and reliability, highlighting its scalability and robustness. Key variables include failure time distributions and stress level variances. The empirical significance suggests that AENST effectively addresses the complexity of multiple stress levels, supporting its application in high reliability testing environments. This finding highlights the potential of AENST in improving the accuracy of GOF testing, bridging the gap in previous research concerning stress level integration.

4.2 Performance of AENST Compared to CPITT

This result supports Hypothesis 2, which states that AENST is superior to CPITT in terms of model validation for AFT models. The comparative analysis shows that AENST yields more accurate and reliable results in most scenarios, especially in complex model structures. The key variables are the validation results and model complexity. The empirical significance further strengthens the superiority of AENST in GOF testing, thus making it more applicable in reliability engineering. This finding addresses previous gaps in comparative analyses, which highlights the superiority of AENST over traditional methods.

4.3 AENST's Application to Weibull Distribution

This finding validates Hypothesis 3, showcasing AENST's robust validation capabilities for Weibull distributions in AFT models. The analysis of simulation data demonstrates consistent accuracy and reliability, even under varying parameter sets. Key variables include parameter variations and validation metrics. The empirical significance suggests that AENST effectively handles the complexities of Weibull distributions, supporting its application in diverse reliability testing scenarios. This finding emphasizes the potential of AENST in improving the accuracy of GOF testing for Weibull distributions by filling in the gaps of previous robustness.

4.4 Application of AENST to Exponential Distribution

This finding supports Hypothesis 4, showing that AENST is useful in confirming exponential distributions in AFT models. The analysis shows that AENST maintains high accuracy and reliability even in challenging model conditions. Key variables include model parameters and validation outcomes. The empirical significance suggests that AENST effectively addresses the complexities of exponential distributions, supporting its application in diverse reliability testing environments. By addressing previous gaps in practical validation, this finding underscores AENST's potential in enhancing GOF testing accuracy for exponential distributions.

4.5 AENST's Effectiveness in Real Data Scenarios

This finding validates Hypothesis 5, highlighting AENST's effectiveness in real-world data applications for AFT models. The analysis of real data sets demonstrates its robust validation capabilities, providing reliable insights into model performance. Key variables include real data parameters and validation outcomes. The empirical significance suggests that AENST effectively handles the complexities of real-world data, supporting its application in practical reliability testing scenarios. By addressing previous gaps in real data application, this finding underscores AENST's potential in enhancing GOF testing accuracy in real-world contexts**.**

5. Conclusion

This study evaluates the adapted extended Neyman's smooth test (AENST) in the context of accelerated failure time (AFT) models, demonstrating its effectiveness in handling multiple stress levels, outperforming CPITT, and providing robust validation for Weibull and exponential distributions, as well as in real data scenarios. The findings emphasize AENST's potential in enhancing GOF testing accuracy, offering practical and theoretical insights into reliability testing. However, the study acknowledges limitations, including the reliance on simulated data and the need for broader real-world validation. Future research should explore the application of AENST across different industries and stress conditions, expanding the scope of its applicability and further refining its methodology for enhanced reliability testing.

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