

Al-Azhar University
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## BAYESIAN AND NON BAYESIAN APPROACH UNDER ACCELERATED LIFE TESTING FOR GENERALIZED INVERSE GAUSSIAN DISTRIBUTION

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To my parents, to my husband and to my beloved sons



## **ABSTRACT**

With rapidly changing technologies, higher customer expectations for better reliability, need rapid device development and the necessity and the creativeness of more advanced technology in manufacturing field. In the traditional life data analysis, time-to-failure (of a product, system or component) data, obtained under usage conditions are analyzed in order to quantify the life characteristics and to make prediction about products performance. In many situations and for many reasons, it may be difficult or even impossible to obtain such life data. Therefore, in order to observe product failures for analyzing their failure modes and understanding their life characteristics in a short time, accelerated life tests (ALT) are developed.

ALT is usually conducted by subjecting the product (or component) to severe conditions than those the product will be experiencing at normal conditions or by using the product more intensively than in normal use without changing the normal operating conditions. Through ALT, stress levels which accelerate product failure are increased and life data for the product under accelerated stress conditions are captured. Those failure data under accelerated stress conditions are then utilized to derive failure information under usage condition based on some life-stress relationship. Thus, ALT for a product or material is often used to quickly obtain information on the life distribution or product performance under usage conditions.

In ALT data analysis, we need to determine the pdf at normal use conditions from ALT data instead of from regular failure data obtained under normal use conditions. In order to do that, we must have an underlying life distribution and a life-stress relationship.

In this thesis, we assumed failure times at each stress level to be inverse Gaussian (IG) distribution with parameter  $\mu$  related to the stress through inverse power law model. For constant stress ALT (CSALT), the maximum likelihood estimators of the model parameters, Fisher information matrix, the asymptotic variance-covariance matrix, the confidence bounds, the predictive value of the parameter  $\mu$  and the reliability function under usual conditions were obtained under both Type-I and Type-II censoring in Chapter 2. Moreover, the optimal design of the ALT was studied according to the A-optimality criterion. A-optimality criterion for choosing the optimal values of the censored time corresponding to Type-I censoring,

the optimal values of sample sizes at each stress level corresponding to Type-II censoring are described. Also, in case of CSALT, numerical simulation and an illustrative real example are presented for illustration the proposed procedure by considering three stress levels.

Also, Bayesian analysis is presented under Type-II censoring for CSALT in Chapter 3. Markov Chain Monte Carlo (MCMC) simulation algorithm based on Gibbs sampling and WINBUGS software enhance the flexibility of the proposed method developed to estimate the unknown parameters of interest in case of both non-informative and informative priors. Moreover, confidence intervals are constructed and the value of the parameter  $\mu$  under usual conditions is predicted. Also, in this case, numerical simulation and an illustrative real example are presented for illustrating the proposed procedure by considering three stress levels.

Finally, the statistical inference of ALT under both Type-I and Type-II censoring for simple Step Stress ALT (SSALT) is discussed in Chapter 4. The maximum likelihood estimators of the model parameters, Fisher information matrix, the asymptotic variance-covariance matrix, the confidence bounds, the predictive value of the parameter  $\mu$  and the reliability function under usual conditions are obtained. Moreover, the optimal design of the ALT is studied according to the A-optimality criterion. This criterion is used for determining the optimum time of changing stress value and censored time only under Type-I censoring. Also, in case of SSALT, numerical simulation is introduced to illustrate the proposed procedure by considering two stress levels.

## ABBREVIATIONS AND SYMBOLS

ALT Accelerated life tests

CE Cumulative exposure

CDF Cumulative distribution function

CI Confidence interval

CSALT Constant stress accelerated life tests

CSPALT Constant stress partially accelerated life tests

FALT Fully accelerated life tests

GIG Generalized inverse Gaussian

GAV Generalized asymptotic variance

HALT Highly accelerated life testing

HASS Highly accelerated stress screening

IG Inverse Gaussian

LS Least Squares

LB Lower bound

MCMC Markov Chain Monte Carlo
MC error Monte Carlo standard error

ML Maximum likelihood

MLSE Modified least squares estimators

MLEs Maximum likelihood estimators

MSE Mean squared errors

PALT Partially accelerated life testing

Pdf Probability density function

PH Proportional hazards

PWM Probability weighted moment

PSALT Progressive stress accelerated life tests

RAB Relative absolute biases

 $R(t_0)$  Reliability function

SD Standard deviation

SSALT Step stress accelerated life tests

SSPALT Step stress partially accelerated life tests

# **ABBREVIATIONS AND SYMBOL (Cont.)**

T-H Temperature-humidity

T-NT Temperature-non-thermal

UB Upper bound

WLS Weighted least squares

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