

Article

Reliability Assessment Method for DC/DC Converters of AgO-Al Batteries

Hongyu Wang ¹, Huajun Gao ¹, Jie Wen ¹ and Shihu Xiang ^{2,*}¹ Tianjin Institute of Power Sources, Tianjin 300384, China; by1414115@buaa.edu.cn (H.W.); daydayup896@126.com (H.G.); wenjie_008@126.com (J.W.)² Key Laboratory of Electromagnetic Field and Electrical Apparatus Reliability of Hebei Province, Hebei University of Technology, Tianjin 300401, China

* Correspondence: 2020070@hebut.edu.cn

Abstract

Silver oxide–aluminum (AgO–Al) batteries are widely used as power sources for underwater vehicles, where direct current/direct current (DC/DC) converters play a critical role in supplying low-voltage loads. Accurate reliability assessment of DC/DC converters is essential for ensuring successful missions. Existing studies rarely consider the constraints between key performance parameters, as well as the load-dependent characteristics of measurement errors, limiting their applicability to DC/DC converters. To address these issues, a probabilistic model describing the relationship between operating load and measurement error is proposed, with particular emphasis on the load-dependent stochastic characteristics of measurement errors. Based on this relationship, load-dependent stochastic models for both the power-on and power-off voltages are developed by jointly considering unit-to-unit variability and random measurement errors. The model parameters are estimated by maximum likelihood estimation. A failure criterion incorporating the operational constraints between the power-on and power-off voltages is established according to the practical requirements of DC/DC converters. A reliability assessment method considering the dependence between the power-on and power-off voltages is provided according to the practical requirements. Based on test data, the results show that the Kolmogorov–Smirnov statistic of the proposed method is at least 86% lower than the compared methods, indicating a more accurate reliability assessment.

Keywords: DC/DC converter; reliability assessment; load-dependent measurement error; performance parameter constraint



Academic Editor: Andrea Gaetano Chiariello

Received: 29 June 2026

Revised: 1 August 2026

Accepted: 6 August 2026

Published: 7 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

1.1. Motivation

Silver oxide–aluminum (AgO–Al) batteries are widely regarded as critical power sources for underwater vehicles because of their high specific energy and high specific power [1–3]. In an AgO–Al battery system, the direct current/direct current (DC/DC) converter plays a key role in converting the high bus voltage supplied to the propulsion motor into a lower voltage required by low-voltage onboard loads, such as servos and monitoring instruments. These loads are essential for attitude adjustment and condition monitoring. Once the DC/DC converter fails, the low-voltage loads may lose power and cease functioning, potentially resulting in mission failure. Therefore, ensuring the reliability of the DC/DC converter is of great significance for the stable and safe operation of underwater vehicles.

In practical applications, the load current of the DC/DC converter varies with operating conditions. Accordingly, reliability assessment of DC/DC converters in AgO-Al battery systems requires performance data collected under different load currents. However, due to the effects of measuring instruments, environmental disturbances, and other internal and external factors, measurement errors are inevitably introduced into the observed data, thereby increasing the uncertainty of reliability assessment results [4]. Moreover, for the DC/DC converter, different load currents may induce different levels of thermal disturbance and electromagnetic interference in the measurement system, resulting in load-current-dependent measurement errors [5–7]. Therefore, when conducting reliability modeling and assessment for DC/DC converters, it is necessary to explicitly consider the influence of actual load currents on measurement errors.

For DC/DC converters used in AgO-Al batteries, the performance parameters include power-on voltage, power-off voltage, and output voltage. Since the output voltage of DC/DC converters is relatively stable and essentially unaffected by load currents, this study focuses on the two key performance parameters, i.e., the power-on voltage and the power-off voltage. If either the power-on voltage or the power-off voltage reaches its threshold, the DC/DC converter is considered to have failed. Moreover, the DC/DC converters in AgO-Al batteries are subject to an additional operational constraint. During the initial activation stage, the AgO-Al battery cannot continuously sustain a load. If the difference between the power-on voltage and power-off voltage of the DC/DC converter is too small, it may lead to the shut down and restart cycles of the DC/DC converter, thereby delaying or even preventing successful mission. Thus, the difference between the power-on voltage and the power-off voltage must satisfy a specific constraint. If this difference falls below a critical value, the DC/DC converter should also be considered failed. This characteristic highlights the necessity of developing a reliability modeling method that accounts not only for individual failure thresholds of performance parameters but also for constraints between performance parameters.

1.2. Literature Review

Measurement errors typically exhibit uncertainty, because measuring instruments are susceptible to random fluctuations in environmental factors, such as ambient temperature variations and stochastic electromagnetic noise [8,9]. To depict the randomness of measurement errors, existing studies commonly assume that measurement errors follow certain prescribed probability distributions, such as normal distribution, skew-normal distribution, and Student's *t*-distribution [10,11]. Among these distributions, normal distribution has been extensively adopted because of theoretical foundation and strong empirical fitting capability in engineering data analysis. It has been widely used in degradation modeling, reliability assessment, remaining useful life prediction, and maintenance decision-making. For example, Si et al. modeled measured degradation data by assuming normally distributed measurement errors, and analyzed their influence on reliability assessment [12]. Li et al. proposed an accelerated degradation model that accounted for the effects of stress and random measurement errors, where the errors were assumed to obey an independent identical normal distribution, and they validated the superior fitting performance using accelerated degradation test data of cables [13]. Wang et al. [14] and Li et al. [15] also employed normal distributions for modeling measurement errors, and they indirectly verified this assumption by accurate remaining useful life predictions and favorable reliability assessment results, respectively. Although existing studies have demonstrated their effectiveness in specific application scenarios, these modeling methods of measurement errors are unsuitable for DC/DC converters because of the neglect of the effect of load currents. For a DC/DC converter, measurement errors are subject to thermal disturbance and

electromagnetic interference in the measurement system, which may be varying with load currents [5–7]. Due to the lack of proper models, modeling measurement errors remains a challenge for electronic devices such as DC/DC converters operating under variable working conditions.

For DC/DC converters used in AgO-Al batteries, we focus on the two key performance parameters, i.e., the power-on voltage and the power-off voltage. Existing research on multiple performance parameters typically assigns separate constraints (i.e., failure thresholds) for different performance parameters [16,17]. For instance, Fang et al. [18], Song and Cui [19], and Pan et al. [20] established multivariate degradation models based on inverse Gaussian processes, gamma processes, and Wiener processes, respectively, and these models all assumed an individual failure threshold for each performance parameter. Similarly, Zhai and Ye [21] and Liu et al. [22] also adopted the failure criterion that if any performance parameter reached a prespecified failure threshold, then the product was considered failed. However, the conventional assumption of failure criterion neglects the constraint between performance parameters. For a DC/DC converter, if the difference between the power-on voltage and the power-off voltage is less than a critical value, the DC/DC converter is also considered failed. Therefore, it is important for accurate reliability assessment of DC/DC converters to specify a proper failure criterion by simultaneously considering the failure threshold of each key performance parameter and the critical value of the difference between the performance parameters.

Based on the above literature review, the existing models of measurement errors assign a specific probability distribution to capture the randomness of measurement errors, but they neglect the effect of load currents. Moreover, the existing assumptions of failure criterion consider an individual failure threshold for each performance parameter, but they neglect the constraint between the performance parameters. Table 1 summarizes the limitations of the previous studies.

Table 1. Limitations of previous studies.

	Modeling of Measurement Errors	Assumption of Failure Criterion
Method	Assign a specific probability distribution	Assume an individual failure threshold for each performance parameter
Limitation	Neglects the effect of load currents	Neglects the constraint between the performance parameters

1.3. Contributions and Organization

DC/DC converters are commonly subject to various uncertainties, including random measurement errors, as well as random heterogeneity among individuals incurred by factors such as instability in manufacturing processes and fluctuations in environmental conditions [17,23]. Thus, it is significant for accurate reliability assessment of DC/DC converters to propose probabilistic models to properly capture the effects of uncertainties. The main contributions of this study are summarized as follows.

1. We propose a probabilistic model for the two key performance parameters, namely the power-on voltage and the power-off voltage, by incorporating multi-source effects including actual load current, unit-to-unit heterogeneity, correlation between the two performance parameters, and randomness of measurement errors. In particular, we carefully model the effect of load currents on random measurement errors.
2. According to the operational requirements of DC/DC converters of AgO-Al batteries, we specify the failure criterion by jointly considering the failure threshold of each performance parameter and the special constraint between the performance parameters.

Then, we develop a reliability assessment method for DC/DC converters based on the specified failure criterion.

3. We verify the feasibility and effectiveness of the proposed method using test data from DC/DC converters of the same type. Through case study, we reveal the effect of load current on the stochastic characteristic of measurement errors, and also investigate the variation law of reliability with the change in load current.

The remainder of the paper is organized as below. Section 2 details the modeling assumptions, the reliability assessment method, and the estimation method for the model parameters. Sections 3 and 4 provide the real case analysis. Finally, Section 5 concludes the study.

2. Materials and Methods

2.1. Modeling Assumptions

2.1.1. Operating Principle of the DC/DC Converters of AgO-Al Batteries

The operating principle of the DC/DC converters of AgO-Al batteries is shown in Figure 1. The bus voltage of the battery serves as the input to the DC/DC converter, while the output of the DC/DC converter provides power to the low-voltage loads. The power-on voltage and power-off voltage of the DC/DC converter can be explained with reference to Figure 2. As the input voltage of the DC/DC converter continues to increase, the power-on voltage is defined as the input voltage corresponding to the moment when the output voltage reaches the required value. Similarly, as the input voltage continuously decreases, the power-off voltage is defined as the input voltage corresponding to the moment when the output voltage falls below the required value.

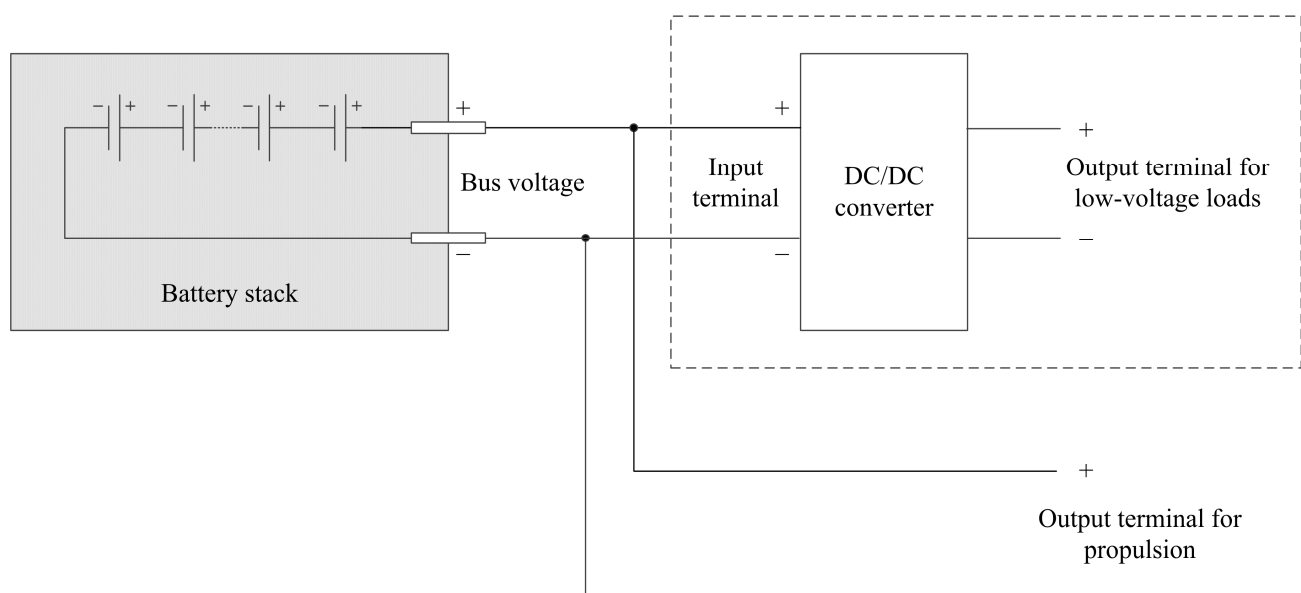


Figure 1. Operating principle of the DC/DC converter of AgO-Al batteries.

When analyzing the reliability of the DC/DC converter, several key aspects need to be carefully considered. Firstly, during the initial activation stage, the AgO-Al battery is incapable of stable loading. To ensure the stability of the output, the power-on voltage and power-off voltage of the DC/DC converter must not be too close to each other. Thus, when analyzing the reliability of the DC/DC converter, it is necessary to consider the constraint between the performance parameters; that is, the difference between the power-on voltage and the power-off voltage should not be less than a specific critical value. Secondly, the power-on voltage and power-off voltage of the DC/DC converter are closely related to its

load conditions. In actual operation, due to varying working conditions, the load current of the DC/DC converter may exhibit uncertainty. Therefore, when analyzing the reliability of the DC/DC converter, it is essential to comprehensively consider scenarios involving multiple load current conditions.

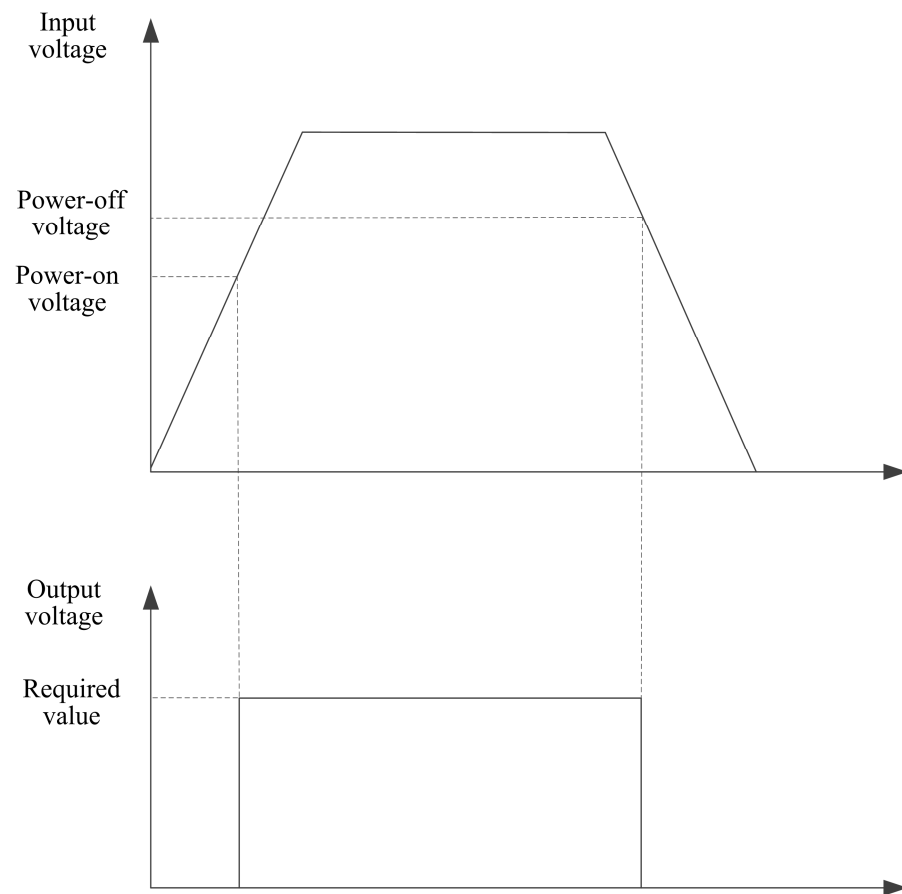


Figure 2. Schematic diagram of power-on voltage and power-off voltage.

2.1.2. Power-On Voltage and Power-Off Voltage Modeling

To comprehensively analyze the reliability of the DC/DC converter under various operating conditions, we first establish the relationship model between the power-on/power-off voltage and the load current. Let $X_1(I)$ and $X_2(I)$ denote the power-on voltage and power-off voltage of the DC/DC converter, respectively, under load current I for $0 \leq I \leq I_U$, where I_U represents the maximum load current of the DC/DC converter, which can be predetermined based on the design inputs. Considering the influence of circuit characteristics, equipment status, etc., the relationship between the power-on/power-off voltage and the load current is expressed as follows.

$$\begin{cases} X_1(I) = g_1(I; \theta_1) + \eta_1, \\ X_2(I) = g_2(I; \theta_2) + \eta_2. \end{cases} \quad (1)$$

For $i = 1, 2$, $g_i(I; \theta_i)$ is the deterministic term determined by circuit characteristics, and represents the deterministic relationship between the power-on/power-off voltage and the load current. θ_i is the parameter vector to be estimated. η_i is a random term following a normal distribution with mean zero and variance $\sigma_{\eta,i}^2$, denoted as $N(0, \sigma_{\eta,i}^2)$, and accounts for unit-to-unit heterogeneity, which primarily arises from instability in manufacturing processes, fluctuations in environmental conditions, etc. [17,23].

To enhance the generality and flexibility of model (1), we assume

$$\begin{cases} g_1(I; \theta_1) = \theta_{1,1} + \theta_{1,2} I^{\theta_{1,3}} \exp(\theta_{1,4} I), \\ g_2(I; \theta_2) = \theta_{2,1} + \theta_{2,2} I^{\theta_{2,3}} \exp(\theta_{2,4} I), \end{cases} \quad (2)$$

where $\theta_i = (\theta_{i,1}, \theta_{i,2}, \theta_{i,3}, \theta_{i,4})'$ for $i = 1, 2$. The functional form of Equation (2) can be simplified into commonly used forms, depending on the values of the model parameters. For example, if $\theta_{i,4} = 0$, Equation (2) reduces to a power-law model, whereas if $\theta_{i,3} = 0$, Equation (2) reduces to an exponential model.

Furthermore, since the power-on voltage and the power-off voltage are influenced by the same electrical principles, there is inevitably a correlation between the two voltages. To characterize the correlation between the power-on voltage and the power-off voltage, we assume that $\eta = (\eta_1, \eta_2)'$ follows a bivariate normal distribution with mean zero and covariance $\Sigma_\eta = [\sigma_{\eta,1}^2, \tau; \tau, \sigma_{\eta,2}^2]$, denoted as $\text{BVN}(0, \Sigma_\eta)$.

During the measurement process, due to the effect of operator actions and operation environment, there are measurement errors between the measured values and the true values. For each measurement, it is assumed that the measurement errors are mutually independent. Since the load current inevitably introduces thermal disturbances and electromagnetic interference to the measuring equipment, the measurement error is affected by the load current.

Based on the above analysis, let $Y_1(I)$ and $Y_2(I)$ denote the measured values of the power-on voltage and power-off voltage, respectively. Then, the relationship between the measured values and the true values can be expressed as

$$\begin{cases} Y_1(I) = X_1(I) + \varepsilon_1(I), \\ Y_2(I) = X_2(I) + \varepsilon_2(I), \end{cases} \quad (3)$$

where for $i = 1, 2$, $\varepsilon_i(I)$ represents the measurement error, and follows a normal distribution $N(0, \sigma_{\varepsilon,i}^2(I))$, in which the variance $\sigma_{\varepsilon,i}^2(I)$ is a function of the load current I . The relationship between $\sigma_{\varepsilon,i}^2(I)$ and I is assumed as the following general and flexible form.

$$\begin{cases} \sigma_{\varepsilon,1}^2(I) = a_1 I^{b_1} \exp(d_1 I) + c_1, \\ \sigma_{\varepsilon,2}^2(I) = a_2 I^{b_2} \exp(d_2 I) + c_2, \end{cases} \quad (4)$$

where for $i = 1, 2$, a_i , b_i , c_i , and d_i are model parameters to be estimated. Depending on the different values of a_i , b_i , c_i , and d_i , the relationship between $\sigma_{\varepsilon,i}^2(I)$ and I can be independent, positively correlated, or negatively correlated. For notation simplicity, let $\Phi_i = (a_i, b_i, c_i, d_i)'$ and $\Psi = \{\theta_1, \theta_2, \Sigma_\eta, \Phi_1, \Phi_2\}$.

Based on the above modeling assumptions, given the load current I for $0 \leq I \leq I_U$, it can be derived that the measured values $Y_1(I)$ and $Y_2(I)$ of the power-on voltage and power-off voltage of the DC/DC converter follow a bivariate normal distribution with means, variances, and covariance respectively given by

$$\begin{cases} E(Y_1(I)) = g_1(I; \theta_1), \\ E(Y_2(I)) = g_2(I; \theta_2), \end{cases} \quad (5)$$

$$\begin{cases} \text{Var}(Y_1(I)) = \sigma_{\eta,1}^2 + \sigma_{\varepsilon,1}^2(I), \\ \text{Var}(Y_2(I)) = \sigma_{\eta,2}^2 + \sigma_{\varepsilon,2}^2(I), \end{cases} \quad (6)$$

$$\text{Cov}(Y_1(I), Y_2(I)) = \text{Cov}(\eta_1, \eta_2) = \tau. \quad (7)$$

2.2. Reliability Assessment

For the DC/DC converter of AgO-Al batteries, proper power-on voltage and power-off voltage are two important requirements to ensure the performance in terms of startup speed and operational stability.

Firstly, if the power-on voltage is too high, the startup of the low-voltage loads will be delayed. Meanwhile, if the power-off voltage is too high, the anti-interference capability of the DC/DC converter will be lowered. Therefore, for any load current, both the power-on voltage and power-off voltage of the DC/DC converter need to be lower than specific thresholds, which can be expressed as

$$X_1(I) < D_1, X_2(I) < D_2, \quad (8)$$

where $X_1(I)$ and $X_2(I)$ can be specified according to Equation (1), and D_1 and D_2 are the failure thresholds of the power-on voltage and the power-off voltage, respectively.

Secondly, in the early stage of activation, AgO-Al batteries are incapable of loading steadily and continuously. Once the DC/DC converter powers on, the bus voltage of the battery will be pulled down. If the difference between the power-on voltage and the power-off voltage is too small, the bus voltage might drop down to the threshold of the power-off voltage. Meanwhile, the DC/DC converter stops outputting power, and then restarts, which would delay the activation of the system. Therefore, to ensure a stable output voltage, the difference between the power-on voltage and the power-off voltage should be larger than a critical value, which can be expressed as the following constraint:

$$X_1(I) - X_2(I) > D_3, \quad (9)$$

where $X_1(I)$ and $X_2(I)$ can be specified according to Equation (1), and D_3 is the failure threshold of the difference between the power-on voltage and the power-off voltage.

Based on the above analysis, given any load current I for $0 \leq I \leq I_U$, the reliability of the DC/DC converter can be expressed as the probability with which the power-on voltage is less than the failure threshold, the power-off voltage is less than the failure threshold, and the difference between the power-on voltage and power-off voltage is larger than the failure threshold. Mathematically, the reliability $R(I)$ can be expressed as

$$\begin{aligned} R(I) &= \Pr(X_1(I) < D_1, X_2(I) < D_2, X_1(I) - X_2(I) > D_3) \\ &= \Pr(\eta_1 < D_1 - g_1(I; \theta_1), \eta_2 < D_2 - g_2(I; \theta_2), \\ &\quad \eta_2 - \eta_1 < -D_3 + g_1(I; \theta_1) - g_2(I; \theta_2)). \end{aligned} \quad (10)$$

Since the vector $\boldsymbol{\eta} = (\eta_1, \eta_2)'$ follows a bivariate normal distribution as described in Section 2.1.2, the vector $\boldsymbol{\eta}^* = (\eta_1, \eta_2, \eta_2 - \eta_1)'$ follows a multivariate normal distribution $\text{MVN}(0, \boldsymbol{\Sigma}_{\boldsymbol{\eta}}^*)$, where $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^*$ is the covariance matrix written as

$$\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^* = \begin{bmatrix} \sigma_{\eta,1}^2 & \tau & \sigma_{\eta,1}^2 - \tau \\ \tau & \sigma_{\eta,2}^2 & \tau - \sigma_{\eta,2}^2 \\ \sigma_{\eta,1}^2 - \tau & \tau - \sigma_{\eta,2}^2 & \sigma_{\eta,1}^2 + \sigma_{\eta,2}^2 - 2\tau \end{bmatrix}. \quad (11)$$

For ease of expression, let $\boldsymbol{\omega} = (D_1 - g_1(I; \theta_1), D_2 - g_2(I; \theta_2), -D_3 + g_1(I; \theta_1) - g_2(I; \theta_2))'$. Then, according to Equation (10), the reliability of the DC/DC converter under load current I for $0 \leq I \leq I_U$ can be expressed as

$$\begin{aligned} R(I) &= \Pr(\boldsymbol{\eta}^* < \boldsymbol{\omega}) \\ &= \int_{\boldsymbol{\eta}^* < \boldsymbol{\omega}} \frac{1}{(2\pi)^{3/2} \sqrt{|\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^*|}} \exp\left[-\frac{1}{2} \boldsymbol{\eta}' (\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^*)^{-1} \boldsymbol{\eta}\right] d\boldsymbol{\eta}. \end{aligned} \quad (12)$$

2.3. Parameter Estimation

This section provides the maximum likelihood estimation (MLE) method for the model parameters based on the test data of n DC/DC converters collected under m load currents. Here, MLE is one of the most used estimation methods in reliability studies [24].

Suppose that the power-on and power-off voltages of the DC/DC converters are tested under m load currents. For load current I_j with $0 \leq I_j \leq I_U$, $j = 1, 2, \dots, m$, each of the n DC/DC converter is measured, and the measurement values are denoted as $Y_{i,k}(I_j)$, $i = 1, 2$, $k = 1, 2, \dots, n$. For notation convenience, the measured data of the DC/DC converters under load current I_j is denoted as $\mathbf{Y}_j = [Y_{1,1}(I_j), Y_{1,2}(I_j), \dots, Y_{1,n}(I_j), Y_{2,1}(I_j), Y_{2,2}(I_j), \dots, Y_{2,n}(I_j)]'$, and then the joint probability density function (PDF) $f(\mathbf{Y}_j; \boldsymbol{\Psi})$ of $\mathbf{Y}_j$ is a multivariate normal distribution. The mean and the covariance matrix are expressed as

$$\boldsymbol{\mu}(I_j; \boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = (g_1(I_j; \boldsymbol{\theta}_1) \mathbf{1}_{1 \times n}, g_2(I_j; \boldsymbol{\theta}_2) \mathbf{1}_{1 \times n})' \quad (13)$$

and

$$\boldsymbol{\Pi}(I_j; \boldsymbol{\Sigma}_\eta, \boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2) = [(\pi_j)_{p,q}]_{2n \times 2n}, \quad (14)$$

respectively, where

$$(\pi_j)_{p,q} = \begin{cases} \sigma_{\eta,1}^2 + \sigma_{\varepsilon,1}^2(I_j), & p = q = 1, 2, \dots, n, \\ \sigma_{\eta,2}^2 + \sigma_{\varepsilon,2}^2(I_j), & p = q = n+1, \dots, 2n, \\ \sigma_{\eta,1}^2, & p, q = 1, 2, \dots, n, p \neq q, \\ \sigma_{\eta,2}^2, & p, q = n+1, \dots, 2n, p \neq q, \\ \tau, & p = 1, 2, \dots, n, q = n+1, \dots, 2n, \\ \tau, & p = n+1, \dots, 2n, q = 1, 2, \dots, n. \end{cases} \quad (15)$$

Given the test data $\mathbf{D} = [(\mathbf{Y}_1)', (\mathbf{Y}_2)', \dots, (\mathbf{Y}_m)']'$, the likelihood function and the log-likelihood function are expressed as

$$\begin{aligned} L(\boldsymbol{\Psi}; \mathbf{D}) &= \prod_{j=1}^m f(\mathbf{Y}_j; \boldsymbol{\Psi}) \\ &= \prod_{j=1}^m (2\pi)^{-n} |\boldsymbol{\Pi}(I_j; \boldsymbol{\Sigma}_\eta, \boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2)|^{-1/2} \\ &\quad \exp\left\{-\frac{1}{2} [\mathbf{Y}_j - \boldsymbol{\mu}(I_j; \boldsymbol{\theta}_1, \boldsymbol{\theta}_2)]' [\boldsymbol{\Pi}(I_j; \boldsymbol{\Sigma}_\eta, \boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2)]^{-1} [\mathbf{Y}_j - \boldsymbol{\mu}(I_j; \boldsymbol{\theta}_1, \boldsymbol{\theta}_2)]\right\} \end{aligned} \quad (16)$$

and

$$\begin{aligned} l(\boldsymbol{\Psi}; \mathbf{D}) &= \ln(L(\boldsymbol{\Psi}; \mathbf{D})) \\ &= -mn \ln(2\pi) - \frac{1}{2} \sum_{j=1}^m \ln |\boldsymbol{\Pi}(I_j; \boldsymbol{\Sigma}_\eta, \boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2)| \\ &\quad - \frac{1}{2} \sum_{j=1}^m [\mathbf{Y}_j - \boldsymbol{\mu}(I_j; \boldsymbol{\theta}_1, \boldsymbol{\theta}_2)]' [\boldsymbol{\Pi}(I_j; \boldsymbol{\Sigma}_\eta, \boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2)]^{-1} [\mathbf{Y}_j - \boldsymbol{\mu}(I_j; \boldsymbol{\theta}_1, \boldsymbol{\theta}_2)], \end{aligned} \quad (17)$$

respectively.

The estimates of $\boldsymbol{\Psi}$ are obtained by maximizing the log-likelihood function. Here, we adopt the genetic algorithm (GA) to compute the estimates for twofold reasons. Firstly, gradient-based algorithms and many other conventional numerical optimization methods are sensitive to the initial guess, whereas GA can mitigate this problem through population-based initialization. Secondly, compared with other evolutionary algorithms, such as particle swarm optimization algorithms, GA often demonstrates a more powerful global search capacity for complex optimization problems [25]. Then, by substituting the parame-

ter estimates into Equation (12), the reliability of the DC/DC converters under any load current I for $0 \leq I \leq I_U$ can be obtained.

3. Results

In this section, the proposed method is demonstrated and compared with recent representative methods based on test data from 20 DC/DC converters of the same type. For the DC/DC converters, the thresholds of the power-on voltage and the power-off voltage are 60.5 V and 48 V, respectively, which are specified according to experimental observations. In addition, to rapidly provide stable power to the low-voltage loads in a short time at the activation stage of the AgO-Al batteries, the power-on voltage of the DC/DC converters need to be 12.5 V higher than the power-off voltage, which is specified according to experimental observations. The tests are conducted under nine load current conditions, 0 A (no-load current), 4 A, 7 A, 10 A, 13 A, 16 A, 19 A, 22 A and 25 A (full-load current), and the measured power-on voltages and power-off voltages of the DC/DC converters are shown in Figures 3 and 4, respectively. Additionally, all the computed results in this study are obtained by MATLAB R2017a.

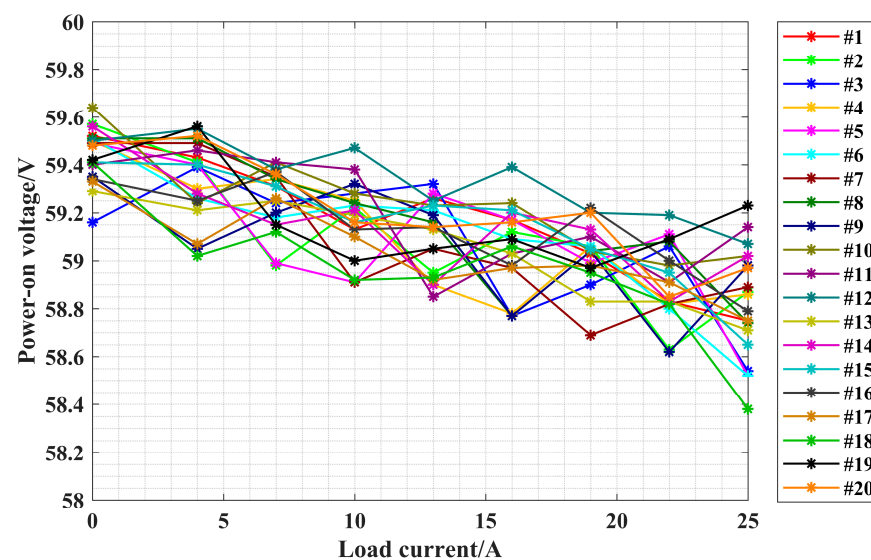


Figure 3. Test data of power-on voltages for the 20 DC/DC converters.

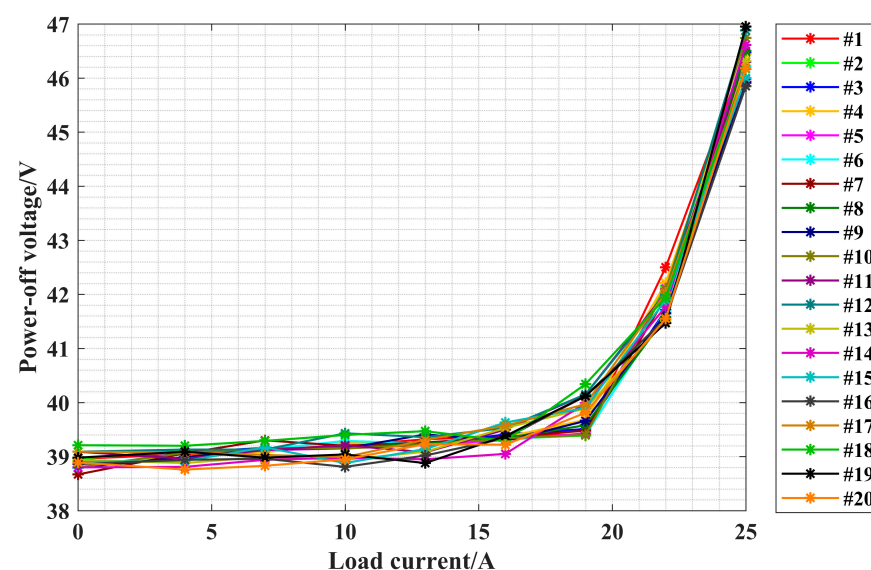


Figure 4. Test data of power-off voltages for the 20 DC/DC converters.

Firstly, to assess the appropriateness of the normality assumption, the Shapiro–Wilk (SW) test is employed to evaluate the normality of the measured data under each load current condition [26]. The p -values are presented in Table 2.

Table 2. p -Values of SW test.

Load Current Conditions	Power-On Voltages	Power-Off Voltages
0 A	0.2373	0.0751
4 A	0.1566	0.2491
7 A	0.0678	0.1322
10 A	0.3509	0.5501
13 A	0.0792	0.4351
16 A	0.1771	0.0920
19 A	0.0879	0.0571
22 A	0.3597	0.4070
25 A	0.9388	0.5251

We conduct parameter inferences using the test data shown in Figures 3 and 4. Table 3 presents the estimates of the model parameters. Then, we compare the estimated average and measured average of the power-on voltage, as well as the estimated average and measured average of the power-off voltage in Figures 5 and 6, respectively. In addition, the estimated variances of the measurement errors are shown in Figure 7.

Table 3. Estimates of the model parameters.

Model Parameters	Estimates
θ_1	$(59.429, -0.025, 1.003, -1.642 \times 10^{-4})'$
θ_2	$(39.011, 0.002, 5.556 \times 10^{-4}, 0.329)'$
Σ_η	$[0.055, -0.131; -0.131, 0.312]$
Φ_1	$(0.001, 0.942, 0.015, 1.051 \times 10^{-4})'$
Φ_2	$(3.398 \times 10^{-5}, 2.425, 0.013, 0.001)'$

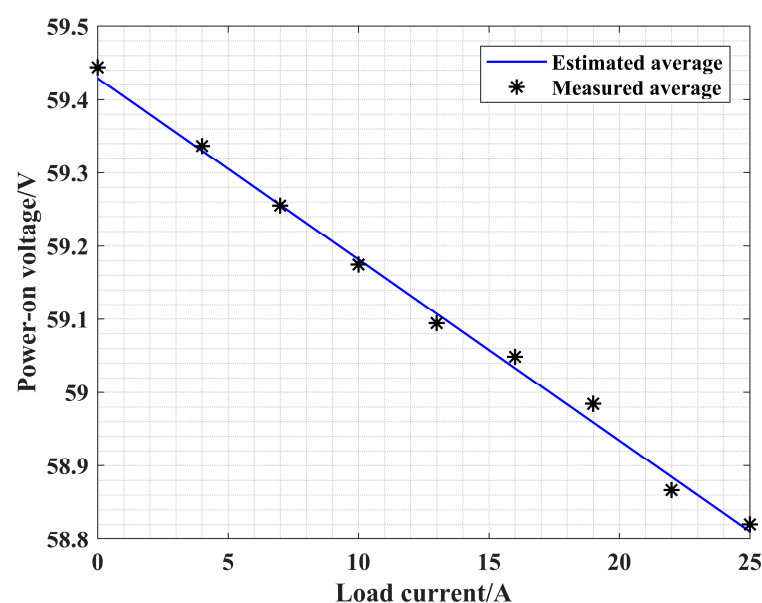


Figure 5. Estimated average and measured average of power-on voltage.

To better exhibit the superiority of the proposed model, we compare the proposed model with three existing models.

Model I: The measurement errors are assumed to follow the same normal distribution [9], and the rest of the model is consistent with the proposed model. Additionally, to conduct GA for parameter estimation, we set population size, crossover rate, mutation rate, maximum generation number, and fitness tolerance to 200, 0.8, 0.01, 500, 10^{-6} , respectively.

Model II: There is no constraint on the difference between the power-on voltage and the power-off voltage [10], and the rest of the model is consistent with the proposed model.

Model III: The measurement errors are assumed to follow the same normal distribution [9], there is no constraint between the power-on voltage and the power-off voltage [10], and the rest of the model is consistent with the proposed model.

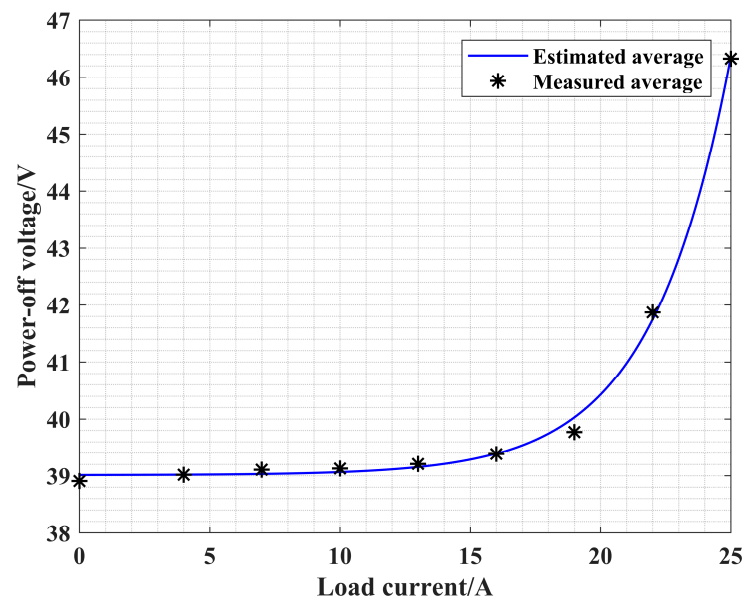


Figure 6. Estimated average and measured average of power-off voltage.

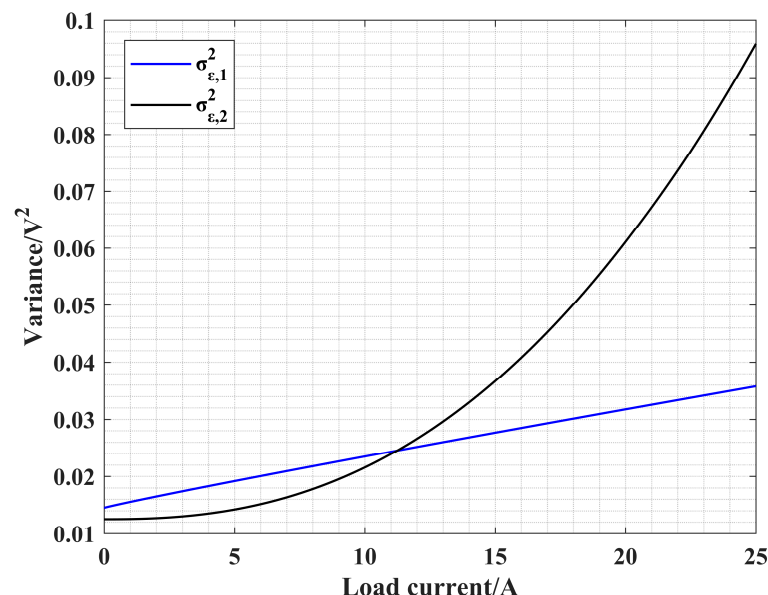


Figure 7. Estimated variances of measurement errors.

Akaike information criterion (AIC) is used to compare the goodness of fit of the four models, and the AIC value is the lower the better [27]. The AIC value is expressed as

$$\text{AIC} = 2k - 2l, \quad (18)$$

where l represents the log-likelihood function, and k is the number of the model parameters. The AIC values of the four models are listed in Table 4. As shown in the table, the AIC values of the proposed model and Model II are identical. This is because the two models share the same representations for the variation in the power-on voltage with load current, the variation in the power-off voltage with load current, and the influence of the load current on measurement errors. The only difference between these models lies in the assumption of the failure criterion. Therefore, they yield the same AIC values. Similarly, the AIC values of Model I and Model III are also identical.

Table 4. Calculation results of AIC values.

	Proposed Model	Model I	Model II	Model III
AIC	−184.273	−138.912	−184.273	−138.912

Furthermore, the four models are used to estimate the reliability of the DC/DC converters, and the results are shown in Figure 8. Take the reliability calculated by the empirical reliability function using the test data under each load current as the benchmark. Then, the Kolmogorov–Smirnov (K-S) statistic is employed to quantitatively compare the accuracy of the estimated results of reliability based on the four models [28]. A smaller value of the K-S statistic indicates a more accurate estimated result [29]. The calculation formula for the K-S statistic is as follows.

$$K-S = \max |R_1 - R_2|, \quad (19)$$

where R_1 is the estimated value and R_2 is the benchmark. The calculation results are listed in Table 5.

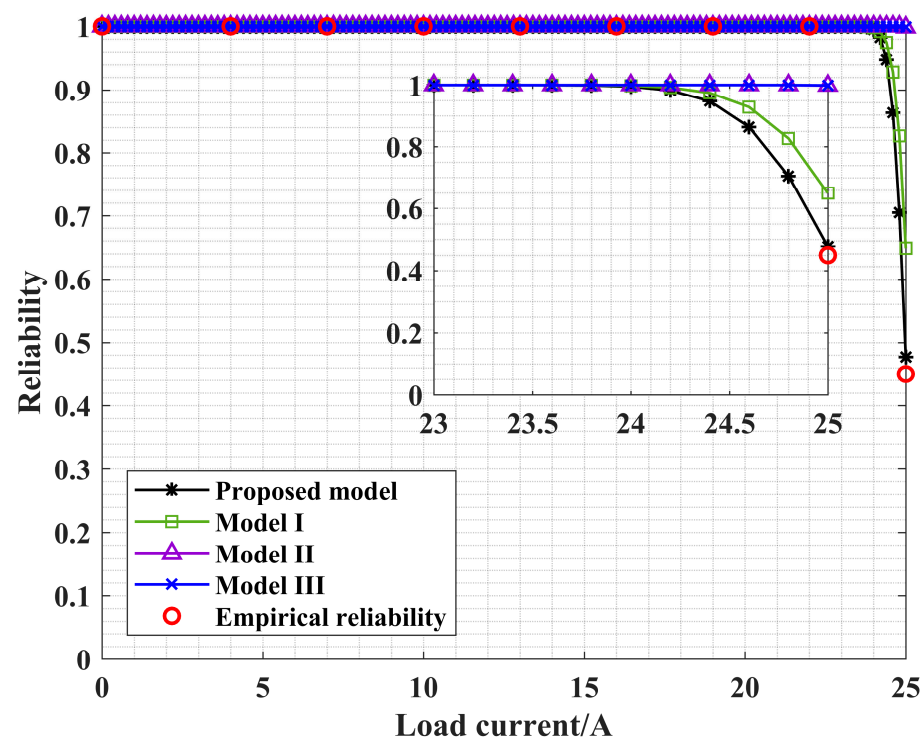
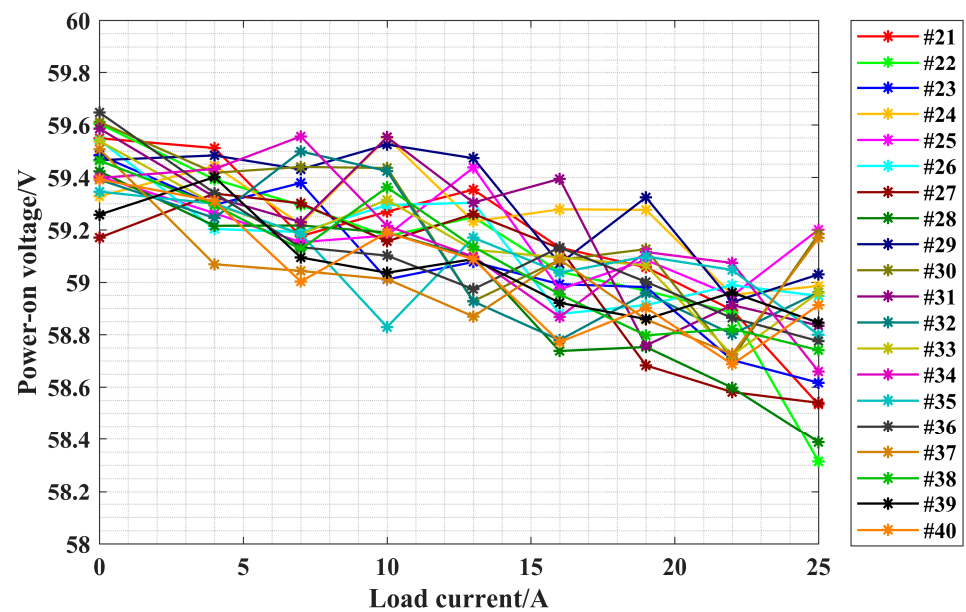
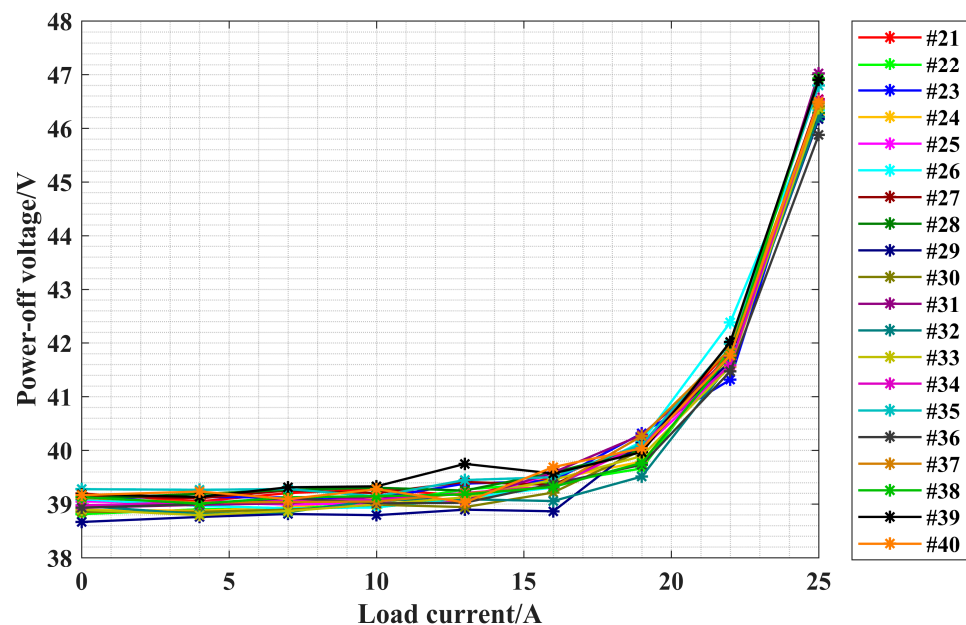


Figure 8. Comparison of the estimated reliability results.

Table 5. Calculation results of K-S statistic.

	Proposed Model	Model I	Model II	Model III
K-S statistic	0.027	0.199	0.548	0.549

Moreover, to illustrate the applicability and generalizability of the estimation results from the proposed model as shown in Figure 8, an independent dataset of 20 additional units is used for cross-validation. The independent dataset is presented in Figures 9 and 10, and the cross-validation result is shown in Figure 11.

**Figure 9.** Test data of power-on voltages for the additional 20 DC/DC converters.**Figure 10.** Test data of power-off voltages for the additional 20 DC/DC converters.

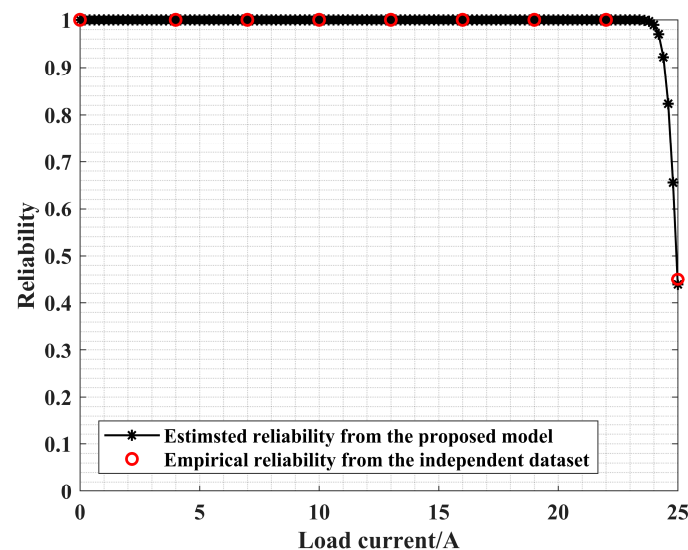


Figure 11. Cross-validation result.

4. Discussion

The measured power-on and power-off voltages are both assumed to be normally distributed variables according to the assumption of normal distributions for unit-to-unit heterogeneity and measurement errors in Equations (1) and (3), respectively. It can be observed from Table 2 that the p -values for the measured power-on and power-off voltages are all greater than 0.05 under each load current condition. Since a p -value larger than 0.05 for SW tests means that the experimental data support the assumption of a normal distribution, it is rational for the proposed model to employ normal distributions to depict unit-to-unit heterogeneity and measurement errors.

From Table 3, we can see that the parameter $\theta_{1,3}$ is close to 1, the parameter $\theta_{1,4}$ approximates to 0, and the parameter $\theta_{1,2}$ is less than 0. This indicates that the power-on voltage and the load current exhibit a linear relationship, and the power-on voltage gradually decreases as the load current increases. The above results coincide with the variation trend of the power-on voltage changing with the load current shown in Figure 3. In addition, the parameters $\theta_{2,2}$ and $\theta_{2,4}$ are greater than 0, and the parameter $\theta_{2,3}$ approximates to 0. This indicates that the power-off voltage and the load current exhibit an exponential relationship, and the power-off voltage increases faster with the rising load current. The above results coincide with the variation trend of the power-off voltage changing with the load current shown in Figure 4.

From Figures 5 and 6, we can see that the average voltage obtained from the proposed model accords with the average from the actual measurement data, which indicates that the proposed model fits the test data well. Moreover, from Figure 7, we can see that the variance of measurement errors gradually increases with the load current. This is because the thermal noise and electromagnetic interference on instruments gradually become stronger as the load current increases, and thus the randomness of measurement errors becomes increasingly larger.

It can be observed from Table 4 that compared with Models I and III, the AIC values of the proposed model and Model II are smaller, indicating a better fit for the test data. This is because different load currents introduce different levels of thermal noise and electromagnetic interference on instruments, thus resulting in different degrees of measurement errors. Model I and Model III fail to account for the impact of the load current on measurement errors, whereas the proposed model and Model II do, and thus fit the data better. In addition, compared with Model II, the proposed model additionally captures the power-off

fault behavior resulting from an excessively small difference between the power-on voltage and the power-off voltage, which is more consistent with reality. Therefore, the proposed model is the best among the four models.

It can be obtained from Table 5 that the K-S statistic of the proposed model is about 86%, 95%, and 95% lower than Models I–III, respectively, indicating that the proposed model achieves the most accurate reliability assessment among the four methods. As can be seen from Figure 8, when the load current is relatively small, the estimated reliability of the proposed model is consistent with the other models. However, as the load current increases, the power-on voltage gradually decreases, while the power-off voltage rises rapidly, which leads to the gap between the two voltages approaching the critical value. Model II and Model III do not consider the constraint on the difference between the power-on voltage and the power-off voltage, thus significantly overestimating the reliability of the DC/DC converters. Additionally, by comparing the reliability results of the proposed model with Model I, it can be found that as the load current increases, if the correlation between the measurement errors and the load current is neglected, the reliability will be overestimated. This is because, compared with the real measurement errors, the assumption in Model I averages the dispersion of measurement errors over different load currents. As a result, at higher load currents, Model I underestimates the dispersion of measurement errors, thereby causing an overestimation of reliability.

Based on the above analysis, Model I, Model II, and Model III all fail to accurately evaluate the reliability of the DC/DC converters, especially under the conditions of high load current. Therefore, the mission and maintenance management based on the evaluation results of these models would increase the risk of system failure. In contrast, the model proposed in this paper takes the effect of the load current on measurement errors into account, and thus captures the randomness of measurement errors more accurately. Meanwhile, the proposed model incorporates the constraint between the power-on voltage and the power-off voltage, enabling a more comprehensive characterization of the failure criteria of the DC/DC converters, thereby ensuring the accuracy of reliability assessment results.

Based on the test data of the 20 DC/DC converters in Figures 3 and 4, we estimate the reliability curve as shown in Figure 8. To further demonstrate the generalizability of the estimated reliability results, we conduct cross-validation, and compare the estimated reliability curve obtained based on the test data of the 20 DC/DC converters in Figures 3 and 4 with the empirical reliability curve obtained based on the test data of the 20 additional DC/DC converters in Figures 9 and 10. It can be observed from Figure 11 that the estimated reliability fits the empirical reliability well, indicating good generalizability to other batches.

The reliability estimation results of the DC/DC converters provide important guidance for reliability-oriented design and maintenance strategies. The results demonstrate that the reliability of a DC/DC converter decreases significantly under high load current conditions. To mitigate this decrease, one potential approach is to improve the uniformity of internal components across different DC/DC converters. Enhancing component uniformity can effectively reduce unit-to-unit heterogeneity among DC/DC converters and weaken performance uncertainty, thereby enhancing reliability. Furthermore, the observed reliability decrease under high-load conditions highlights the necessity of developing load-dependent maintenance strategies. Maintenance frequency and level can be determined according to the actual operating load condition, enabling targeted reliability of a DC/DC converter. Such load-dependent maintenance strategies can reduce unexpected failures and improve availability.

5. Conclusions

In this study, a reliability assessment method for the DC/DC converters in AgO-Al batteries is proposed, innovatively incorporating the constraint between the power-on voltage and the power-off voltage, as well as the impact of the load current on random measurement errors. Firstly, the relationship between the power-on voltage and the load current, and the relationship between the power-off voltage and the load current, are modeled by comprehensively taking the effects of unit-to-unit heterogeneity and random measurement errors into consideration. Then, the model parameters are estimated by using the MLE method through matrix operations, and a reliability calculation method is established by considering the constraint between the power-on voltage and the power-off voltage. In the case study, the effect of the load current on measurement errors is validated, and the results indicate that the spread of measurement errors increases with the load current. In addition, the calculation results show that the K-S statistic of the proposed method is at least 86% lower than the compared methods, indicating a more accurate reliability assessment. Moreover, the comparison of the estimated reliability results demonstrates that the reliability of the DC/DC converters will be overestimated, if the constraint between the power-on voltage and the power-off voltage is ignored. In that way, the mission and maintenance management based on the overestimated result will increase the failure risk of the system mission. Furthermore, the estimated reliability results show that when the load current increases, the reliability of the DC/DC converter rapidly decreases. Thus, to ensure the successful execution of system tasks, it is essential to optimize the DC/DC converter, enhancing its reliability under high load current conditions.

This study is focused on the reliability assessment of DC/DC converters, and provides some suggestions for design and maintenance strategies according to the reliability estimation result. However, how to utilize the reliability assessment result to quantitatively optimize the design and plan maintenance strategies is not discussed in detail. In the future, the optimization method of DC/DC converters can be investigated for high load current conditions, and maintenance strategies based on the proposed reliability assessment methods can be developed for DC/DC converters.

Author Contributions: Conceptualization, H.W. and S.X.; methodology, H.W. and S.X.; software, S.X.; validation, J.W. and S.X.; formal analysis, H.W. and H.G.; investigation, H.W. and J.W.; resources, S.X.; data curation, H.W. and S.X.; writing—original draft preparation, H.W.; writing—review and editing, S.X.; visualization, H.G.; supervision, S.X.; project administration, S.X.; funding acquisition, S.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 72101081.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: Authors Hongyu Wang, Huajun Gao, Jie Wen were employed by the company Tianjin Institute of Power Sources. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AgO-Al	Silver oxide–aluminum
DC/DC	Direct current/direct current
MLE	Maximum likelihood estimation
PDF	Probability density function
GA	Genetic algorithm
SW	Shapiro–Wilk
AIC	Akaike information criterion
K-S	Kolmogorov–Smirnov

References

- Chen, P.; Zheng, Q.; Wang, C.; Dai, P.; Yin, Y.; Chen, J.; Wang, X.; Xu, W.; Ruan, M. Progress in Al/AgO Electrode Materials for Seawater-Activated Batteries. *Energies* **2025**, *18*, 4007. [\[CrossRef\]](#)
- He, X.; Li, Z.; Wang, Y.; Xu, W.; Zhang, Q.; Wang, X.; Liu, H.; Yang, G.; Zhang, H.; Song, J.; et al. A High-Purity AgO Cathode Active Material for High-Performance Aqueous AgO-Al Batteries. *J. Power Sources* **2022**, *551*, 232151. [\[CrossRef\]](#)
- Dou, Z.; Tang, Q.; Du, Z.; Du, Y.; Li, S.; Liu, F. Design and Implementation of an Electrolyte Temperature Control System for AgO-Al Batteries. *Batteries* **2025**, *11*, 244. [\[CrossRef\]](#)
- Whitmore, G.A. Estimating Degradation by a Wiener Diffusion Process Subject to Measurement Error. *Lifetime Data Anal.* **1995**, *1*, 307–319. [\[CrossRef\]](#) [\[PubMed\]](#)
- Kim, J.-A.; Cho, Y.-G.; Choi, H.-G. Switching Techniques for Minimizing Current Measurement Noise in Integrated Single Shunt Power Conversion System with Common DC Link. *IEEE Access* **2024**, *12*, 156893–156903. [\[CrossRef\]](#)
- Joung, H.; Ahn, T.; Cho, M. Internal Power Loss Modeling and Efficiency Evaluation of Full-Bridge DC-DC Converters Based on Load-Current-Dependent Loss Coefficients. *Energies* **2026**, *19*, 899. [\[CrossRef\]](#)
- Dubey, D.; Rincón-Mora, G.A. Quantifying and Correcting Systemic Offset Errors in PWM and Peak-Valley DC-DC Converters. *Electronics* **2026**, *15*, 2271. [\[CrossRef\]](#)
- Zhang, H.; Chen, R.; Chun, S.; Xu, C. A New Calibration Method for Broadband Complex Resistivity Measurement System of Rocks and Ores. *Appl. Sci.* **2025**, *15*, 1526. [\[CrossRef\]](#)
- Afshari, A.; Lee, J.; Besenski, D.; Dimitrijevic, B.; Spasovic, L. Calibrating Microscopic Traffic Simulation Model Using Connected Vehicle Data and Genetic Algorithm. *Appl. Sci.* **2025**, *15*, 1496. [\[CrossRef\]](#)
- Tsai, C.C.; Lin, C.T. Lifetime Inference for Highly Reliable Products Based on Skew-Normal Accelerated Destructive Degradation Test Model. *IEEE Trans. Reliab.* **2015**, *64*, 1340–1355. [\[CrossRef\]](#)
- Zhai, Q.; Ye, Z.S. Robust Degradation Analysis with Non-Gaussian Measurement Errors. *IEEE Trans. Instrum. Meas.* **2017**, *66*, 2803–2812. [\[CrossRef\]](#)
- Si, X.S.; Chen, M.Y.; Wang, W.; Hu, C.H.; Zhou, D.H. Specifying Measurement Errors for Required Lifetime Estimation Performance. *Eur. J. Oper. Res.* **2013**, *231*, 631–644. [\[CrossRef\]](#)
- Li, Y.; Gao, H.; Chen, H.; Liu, C.; Yang, Z.; Zio, E. Accelerated Degradation Testing for Lifetime Analysis Considering Random Effects and the Influence of Stress and Measurement Errors. *Reliab. Eng. Syst. Saf.* **2024**, *247*, 110101. [\[CrossRef\]](#)
- Wang, H.; Liao, H.; Ma, X. Remaining Useful Life Prediction Considering Joint Dependency of Degradation Rate and Variation on Time-Varying Operating Conditions. *IEEE Trans. Reliab.* **2021**, *70*, 761–774. [\[CrossRef\]](#)
- Li, J.; Wang, Z.; Zhang, Y.; Fu, H.; Liu, C.; Krishnaswamy, S. Degradation Data Analysis Based on a Generalized Wiener Process Subject to Measurement Error. *Mech. Syst. Signal Process.* **2017**, *94*, 57–72. [\[CrossRef\]](#)
- Liu, X.; Chen, X.; Wei, Y.; Chen, L.; Gong, S. Study on the Mechanical Characteristics and Degradation Response of Unloading Rocks Surrounding Tunnels in Cold Regions. *Appl. Sci.* **2025**, *15*, 1269. [\[CrossRef\]](#)
- Yan, B.; Wang, H.; Ma, X. Correlation-Driven Multivariate Degradation Modeling and RUL Prediction Based on Wiener Process Model. *Qual. Reliab. Eng. Int.* **2023**, *39*, 3203–3229. [\[CrossRef\]](#)
- Fang, G.; Pan, R.; Wang, Y. Inverse Gaussian Processes with Correlated Random Effects for Multivariate Degradation Modeling. *Eur. J. Oper. Res.* **2022**, *300*, 1177–1193. [\[CrossRef\]](#)
- Song, K.; Cui, L. A Common Random Effect Induced Bivariate Gamma Degradation Process with Application to Remaining Useful Life Prediction. *Reliab. Eng. Syst. Saf.* **2022**, *219*, 108200. [\[CrossRef\]](#)
- Pan, G.; Li, Y.; Li, X.; Luo, Q.; Wang, C.; Hu, X. A Reliability Evaluation Method for Multi-Performance Degradation Products Based on the Wiener Process and Copula Function. *Microelectron. Reliab.* **2020**, *114*, 113758. [\[CrossRef\]](#)

21. Zhai, Q.; Ye, Z.S. A Multivariate Stochastic Degradation Model for Dependent Performance Characteristics. *Technometrics* **2023**, *65*, 315–327. [[CrossRef](#)]
22. Liu, B.; Zhao, X.; Liu, G.; Liu, Y. Life Cycle Cost Analysis Considering Multiple Dependent Degradation Processes and Environmental Influence. *Reliab. Eng. Syst. Saf.* **2020**, *197*, 106784. [[CrossRef](#)]
23. Hao, S.; Yang, J.; Berenguer, C. Nonlinear Step-Stress Accelerated Degradation Modelling Considering Three Sources of Variability. *Reliab. Eng. Syst. Saf.* **2018**, *172*, 207–215. [[CrossRef](#)]
24. Hu, H.; Bao, Y.; Huang, Y.; Xiong, M.; Wang, W. PDET-Based Assumption-Free Method for Efficient Seismic Fragility Assessment of Slopes with Combined Uncertainties of Soil Materials and Input Ground Motions. *Reliab. Eng. Syst. Saf.* **2025**, *261*, 111132. [[CrossRef](#)]
25. Papazoglou, G.; Biskas, P. Review and Comparison of Genetic Algorithm and Particle Swarm Optimization in the Optimal Power Flow Problem. *Energies* **2023**, *16*, 1152. [[CrossRef](#)]
26. Shan, H.-M.; Maurer, M.A.; Schwab, M.E. Four-Parameter Analysis in Modified Rotarod Test for Detecting Minor Motor Deficits in Mice. *BMC Biol.* **2023**, *21*, 177. [[CrossRef](#)] [[PubMed](#)]
27. Xiang, S.; Zhao, C.; Hao, S.; Li, K.; Li, W. A Reliability Evaluation Method for Electromagnetic Relays Based on a Novel Degradation-Threshold-Shock Model with Two-Sided Failure Thresholds. *Reliab. Eng. Syst. Saf.* **2023**, *240*, 109549. [[CrossRef](#)]
28. Lin, Y.H.; Ding, Z.Q. An Integrated Degradation Modeling Framework Considering Model Uncertainty and Calibration. *Mech. Syst. Signal Process.* **2022**, *166*, 108389. [[CrossRef](#)]
29. Dong, W.; Cao, Y.; Ouyang, L. Optimal Test Termination Time in Reliability Growth Management for Systems with Multiple Failure Modes. *Reliab. Eng. Syst. Saf.* **2025**, *263*, 111226. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.