VOL. 22, NO. 1, 2023, 42-52
www.fke.utm.my/elektrika
ISSN 0128-4428

ELEKTRIKA
Journal of Electrical Engineering

A Review of Failure Rate Models for Deterioration in Rural Microgrids: Evaluating Model Complexity and Data Extensiveness

Tinton Dwi Atmaja[1,2,3], Dalila Mat Said[1,3,*], Sevia Mahdaliza Idrus[1,3], Ahmad Fudholi[2,4], Mohd Hafiz Habibuddin[1] and **Ahmad Rajani[1,2,3]**

[1]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia
[2]Research Centre for Energy Conversion and Conservation, BRIN, Bandung, Indonesia
[3]Centre of Electrical Energy System, Institute of Future Energy, UTM, Johor, Malaysia
[4]Solar Energy Research Institute, Universiti Kebangsaan Malaysia, Bangi Selangor, Malaysia

[*]Corresponding author: dalila@utm.my

Abstract: Microgrids in rural areas are crucial for providing reliable and sustainable electricity to remote communities. The deterioration of these microgrids can result in power outages and decreased efficiency. A failure rate model is a tool used to predict and mitigate the risk of deterioration. This study aims to provide a comprehensive overview of various failure rate models for deterioration in rural microgrid systems, with a focus on evaluating the model complexity and data extensiveness. A total of fourteen failure rate models were analyzed based on their complexity and data requirements. Complexity was evaluated in four levels, ranging from simple to expert. Data extensiveness was evaluated in four levels, ranging from basic to expert. The results show that the complexity and extensiveness of the models vary significantly, with some models being more appropriate for certain types of microgrid systems than others. The study also highlights the importance of considering the complexity and extensiveness of a model when selecting it for a particular microgrid system. This study provides valuable insights for policymakers, microgrid engineers, and microgrid operators in selecting the most appropriate failure rate model for their rural microgrid systems. The findings emphasize the need to consider the complexity and extensiveness of the model to ensure its effectiveness and efficiency in predicting and mitigating the risk of deterioration.

Keywords: Failure rate model, microgrid, model complexity, data extensiveness.

Article History: received 19 February 2023; accepted 9 April 2023; published 28 April 2023.

1. INTRODUCTION

Rural microgrid systems have become increasingly important as a means of providing sustainable and reliable energy access to remote areas. With the integration of photovoltaic (PV) panels and energy storage systems, rural microgrid systems have the potential to significantly improve energy access and reduce energy poverty in remote areas [1]. However, the long-term performance and reliability of these systems can be impacted by various types of deterioration, such as the degradation of PV modules, energy storage systems, and the distribution network [2][3].

To ensure the long-term sustainability and reliability of rural microgrid systems, it is important to understand the various mechanisms of deterioration and their impact on system performance [4]. Failure rate models can provide valuable insights into the rate at which various components of the rural microgrid system are likely to fail, and the impact that these failures may have on system performance [5]. This study provides an overview of the various failure rate models that have been developed for rural microgrid systems, with a focus on the comparison of their complexity and extensiveness.

The concept of complexity in failure rate models refers to the level of difficulty in understanding, implementing, and using the model. There are several factors that contribute to the complexity of a model, including the level of mathematical sophistication required, the ease of implementation, and the amount of data required to use the model effectively [6].

Some failure rate models are relatively simple and can be easily understood and applied by those with minimal technical knowledge. These models may be based on simple mathematical equations and use data that is easily obtainable. On the other hand, there are more complex models that require a higher level of mathematical sophistication, data analysis expertise, and computational resources. These models may use more advanced mathematical techniques and may require a significant amount of data to be accurate.

The concept of extensiveness in failure rate models refers to the amount of data required to use the model effectively. This includes data about the microgrid system itself, as well as data about the environmental and operational conditions that the microgrid system is exposed to [7].

There are several levels of data requirements for failure rate models, ranging from basic data that is easily obtained to more extensive data sets that may be difficult to obtain or analyze. Basic models may use limited data, such as historical failure data, to make predictions about future failures. More extensive models, on the other hand, may use a wide range of data, including data on system design, component performance, environmental conditions, and operational data. The comprehensiveness of the data used in a model can greatly impact the accuracy of the model's predictions.

Therefore, the complexity and extensiveness of a failure rate model are important factors to consider when selecting a model for use in a rural microgrid system. These factors can impact the ease of implementation, accuracy, and comprehensiveness of the model, and must be carefully considered when selecting a model for use in a real-world application.

The study is conducted using several approaches, starting with an overviewing the various components of rural microgrid systems and their potential domain of deterioration. This is followed by a review of the various failure rate models that have been developed at previous studies, including those focused on PV module degradation, energy storage system failure, component worn out, transmission line derivation, and distribution network deterioration.

The approaches were described in Section 2, while the complexity and extensiveness of the various failure rate models are observed based mathematical sophistication and data requirements of each model are discussed. Finally, the implications of these findings for policy makers, engineers, and operators working in the field of rural microgrid systems are explored. The paper concludes with a summary of the key findings and recommendations for future research.

2. METHOD AND APPROACHES

This section aims to provide a clear and comprehensive description of the research design and data analysis techniques used to evaluate failure rate models for deterioration in rural microgrids. This section outlines the process of categorizing models into four levels of complexity and data extensiveness, as well as the criteria used to make these evaluations.

2.1 Categorizing Models

In this study, failure rate models for deterioration in rural microgrids were categorized into four levels based on their complexity and data extensiveness. The models were evaluated based on a set of criteria, including mathematical sophistication, the amount and type of data required, and ease of implementation.

2.2 Models Evaluation

In order to evaluate the failure rate models, a comprehensive literature review was conducted. This involved searching academic databases and other relevant sources for relevant articles and studies. The data collected from these sources was analyzed to determine the level of complexity and data extensiveness for each model.

2.2.1 Evaluation of Complexity:

The complexity of the models was evaluated based on a set of criteria, including mathematical sophistication, ease of implementation, and the amount and type of data required. A detailed analysis of the mathematical equations and methodologies used by each model was performed to determine the level of mathematical sophistication. The ease of implementation was evaluated based on the availability of software and tools to implement the model, as well as the level of technical knowledge required.

2.2.2 Evaluation of Data Extensiveness:

The extensiveness of the data required by each model was evaluated based on the amount and type of data required, as well as the level of accuracy and comprehensiveness of the results. The availability of the data and the cost of acquiring the data was also taken into consideration.

2.3 Limitation and Interpretation

Constraint of this study could be the limited availability of data and information on certain models. Some models may not have enough data to accurately evaluate their complexity or extensiveness, which can impact the results and conclusions of the study. Additionally, some models may only be available through commercial sources, which can limit the scope of the study. Another limitation could be the subjectivity of the categorization of the models into different levels of complexity and extensiveness, as

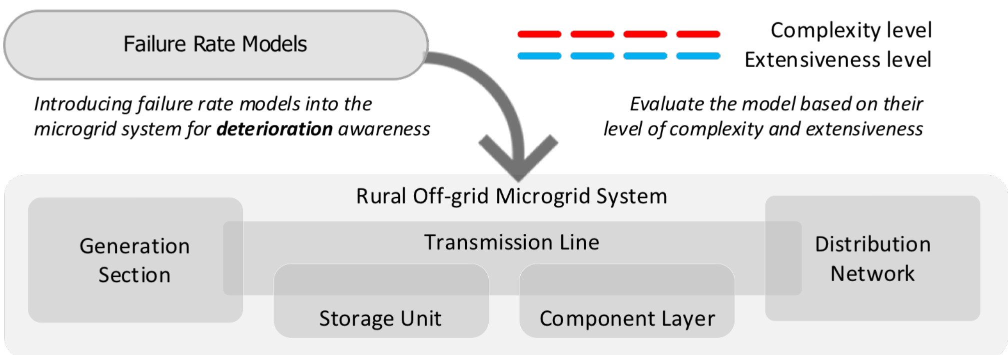

Figure 1. Implementation framework of the models

different side of view may insights different opinions on the criteria for these categorizations.

The results of the analysis were presented in tabular and graphical form, including a comparison of the complexity and extensiveness of each model. The results were then interpreted to provide insights into the strengths and weaknesses of each model and to make recommendations for future research.

In the end, this study of model complexity and data extensiveness provides a useful framework for comparing and contrasting the various failure rate models for deterioration in rural microgrids. The results of this study will be used to inform policy decisions and guide future research in this field.

3. POTENTIAL FAILURE RATE MODELS FOR RURAL MICROGRID DETERIORATION

This section describes the models in regards with rural microgrid deterioration. The study has analyzed a total of eleven different models, which have been addressed to microgrid domains at Figure 1, and describe the models based on their complexity and extensiveness.

3.1 The Bathtub curves

The Bathtub curve is a graphical representation of the failure rate over time, characterized by three stages: an initial high failure rate (infant mortality), a low failure rate (useful life), and an increasing failure rate (wear-out). The Bathtub curve is widely used in reliability engineering to model the expected failure rate of products and systems over time [8][9]. Figure 2 shows the example of the bathtub failure curve [10].

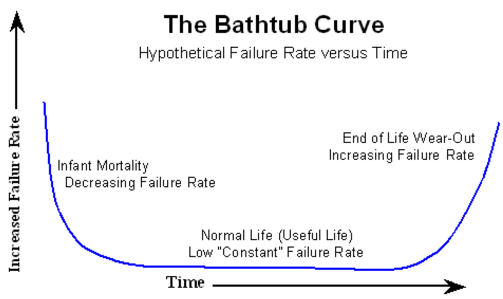

Figure 2. The Bathtub Curve [10]

The bathtub curve model is a semi-empirical model that uses statistical data to describe the expected failure rate of a system over time. It is considered to have an intermediate level of mathematical sophistication, as it requires a basic understanding of statistical concepts and the ability to perform simple data analysis. Based on the literature [10][11], the model should require the historical data on the number of failures for the system (time-to-failure data), the operating conditions of the system or component, such as temperature, humidity, and stress levels, the approximate age of the system or component at the time of failure, and potentially the manufacturing data. The history of repairment and maintenance data should help the model calculation.

In terms of data extensiveness, the bathtub curve model requires an advance amount of data, with a focus on the time-to-failure data. The accuracy and comprehensiveness of the results will depend on the quality and completeness of the data, as well as the ability of the analyst to correctly model the underlying processes and relationships.

3.2 Weibull distribution

Weibull distribution is a statistical distribution often used to model the time-to-failure of products and systems. The Weibull distribution can be used to estimate the probability of failure at a given time, and to predict the failure rate over time [8][12]. For PV implementation has been studied by [13][14].

In the context of microgrid deterioration, the Weibull distribution can be used to estimate the failure rate of the distribution network over time, taking into account factors such as age, environmental factors (such as solar irradiance), captation surface, and usage history [13]. The Weibull distribution can also be used to estimate the remaining useful life of the distribution network and to plan for maintenance and replacement. Figure 3 shows the example of Weibull probability distribution function (pdf) [15].

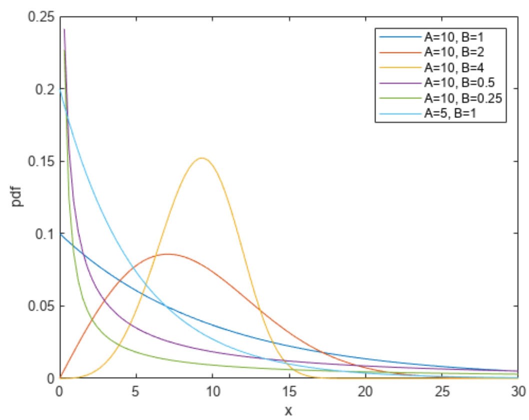

Figure 3. Example of Weibull pdf [15].

The Weibull distribution is a commonly used failure rate model in reliability engineering. It is a mathematical model that can be used to estimate the probability of failure for a component or system over time. The Weibull distribution is a relatively simple model, with a low level of mathematical sophistication. It requires a small amount of data, typically consisting of time-to-failure data for a sample of components or systems, operating time, outages frequency, downtime, and consumer data [16]. The model is easy to implement and can be used to estimate the reliability of a component or system with a high level of accuracy.

In terms of extensiveness, the Weibull distribution model requires a relatively small amount of data to produce accurate results. The model can provide an estimate of the reliability of a component or system with a good level of accuracy and comprehensiveness, especially when the underlying distribution is well-known and the data used is robust. However, if the data used is limited, the results of the Weibull distribution model may be less accurate and comprehensive.

3.3 Markov Chain model

The Markov Chain model is a statistical model that represents the state of a system over time, where the state of the system changes from one time step to the next based on the current state and the transition probabilities between states [17][18]. In the context of microgrid deterioration, the Markov Chain model can be used to represent the state of the microgrid components over time, where the state of each component is defined by its level of degradation or deterioration. The transition probabilities between states can be estimated based on historical data or simulations, and the model can be used to predict the future state of the microgrid components and the expected failure rate over time.

The Markov Chain model is a statistical model that uses probability theory and mathematical sophistication to predict the likelihood of failure over time. It requires a significant amount of data to be inputted, including information about past failures, operating conditions, and other relevant factors [19]. The model is complex to implement, requiring a deep understanding of statistical theory and the ability to run complex mathematical simulations [18]. Figure 4 shows an example of complexity in Markov chain model [20].

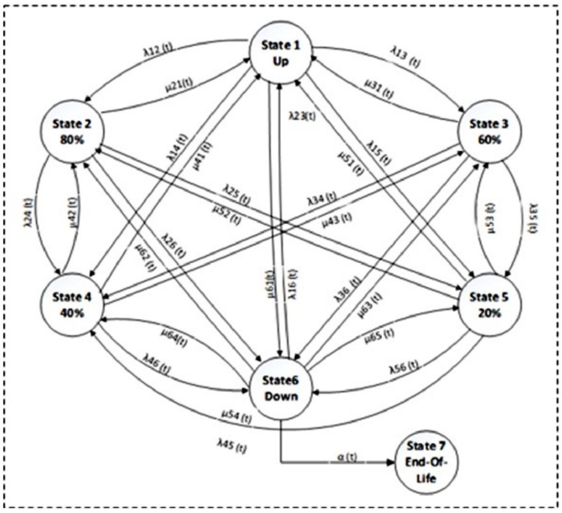

Figure 4. Example of Markov chain model [20].

In terms of data extensiveness, the Markov Chain model requires a large amount of data to be inputted in order to accurately predict the likelihood of failure over time. This data must be comprehensive and relevant to the system being modeled, including information about past failures, operating conditions, and other factors that may impact the system's reliability. The level of accuracy and comprehensiveness of the results will depend on the quality and amount of data inputted, with more extensive data typically leading to more accurate results.

3.4 Battery State of Health (SOH) model

The Battery SOH model is a mathematical model that is used to describe the degradation of batteries over time. The Battery SOH model takes into account factors such as the charge and discharge history of the battery, the temperature and environment in which the battery is operating, and the age of the battery [12][21][22]. The Battery SOH model can be used to estimate the remaining useful life of a storage unit and to plan for maintenance and replacement. Figure 5 shows an example of battery state of health model [23].

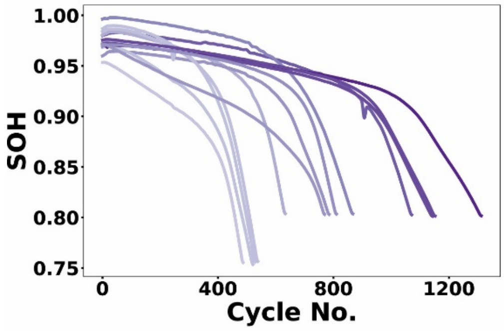

Figure 5. Example of battery state of health model [23]

The Battery State of Health (SOH) model is a relatively simple model that requires relatively limited mathematical sophistication. The model is based on measuring the remaining capacity of a battery, which is a straightforward and easily obtainable value. The amount and type of data required for this model is also relatively limited, typically requiring only battery capacity data over time. Ease of implementation depends on the data collection method and the availability of software or algorithms for calculating the SOH value, but it can generally be considered a straightforward model to implement.

In terms of data extensiveness, the SOH model is relatively limited. The model relies on the accuracy of the battery capacity data, and the level of accuracy and comprehensiveness of the results will depend on the quality and frequency of the data collected. The model may not provide a complete picture of the failure rate of the battery, as it is based on a single value (the remaining capacity).

3.5 Time-to-Failure (TTF) model

The TTF model is a mathematical model that can be used to estimate the time until failure of a component, in this case, the transmission line and storage units [24][25]. The TTF model takes into account factors such as the age of the transmission line, environmental factors, and the historical failure rate of similar transmission lines. The Time-to-Failure (TTF) failure rate model is a statistical model that predicts the time until a component or system fails [26].

This model requires data on the time until failure for each component or system, which can be obtained through field tests, simulations, or historical records. The mathematical sophistication of the TTF model is relatively low, making it easy to implement and understand. In terms of data requirements, the TTF model requires time-to-failure data for each component or system, which can be a large amount of data depending on the number of components or systems being studied. Figure 6 shows an example of the time-varying failure rate of a transistor as one of the microgrid component layer ad also as an important part on many microgrid sections such as in transmission line [27].

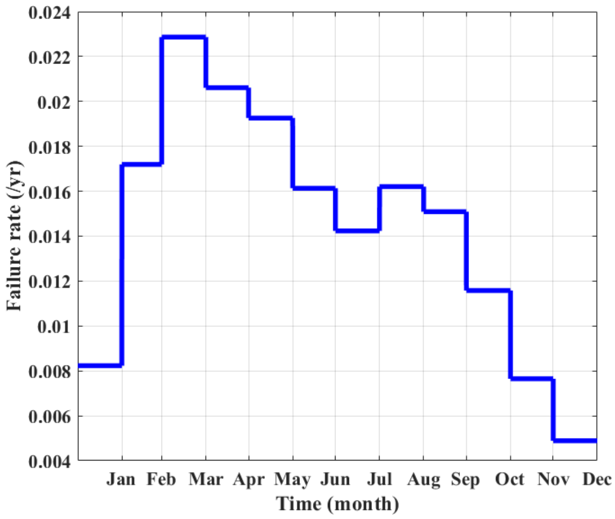

Figure 6. Example of the time-varying failure rate of a transistor component [27]

In terms of data extensiveness, the TTF model requires a significant amount of data on the time until failure for each component or system. The accuracy and comprehensiveness of the results depend on the quality and quantity of the data used in the model. If the data is complete, accurate, and representative, the results of the TTF model can be highly accurate and comprehensive. However, if the data is incomplete, inaccurate, or not representative, the results of the TTF model may be less accurate and comprehensive.

3.6 Arrhenius Equation Model

The Arrhenius equation is a statistical model that is used to describe the temperature dependence of chemical reactions and the rate at which reactions occur. In the context of microgrid deterioration, the Arrhenius equation can be used to estimate the failure rate of solar module [28][29] or storage units [30][31] over time, taking into account the impact of temperature on the performance and reliability of the storage unit.

The Arrhenius equation can be adapted to take into account other factors that impact the reliability of storage units, such as age, environmental factors, and usage history. The example of Arrhenius Equation Model shown in eq. (1) is a relatively simple mathematical model that describes the relationship between temperature and the rate of failure for components [32].

$$f(T) = A_{exp}\left(\frac{-E}{kT}\right) \tag{1}$$

Where $f(T)$ is the degradation, A is pre-exponential factor, E is activated energy, k is Boltzmann constant, and T is component temperature.

This model has a low level of mathematical sophistication, with only basic algebraic equations required for its implementation. The amount of data required is also minimal, with only the temperature data for the components needed. Implementation of the Arrhenius Equation Model is straightforward and can be easily done with basic knowledge of the equation and data input.

In terms of data extensiveness, the Arrhenius Equation Model requires only a limited amount of temperature data. The level of accuracy and comprehensiveness of the results depend on the quality and completeness of the temperature data. Results from this model may not be as comprehensive as those from more complex models, but they can still provide valuable insights into the temperature-failure relationship.

3.7 State-Space model

State-Space model is a mathematical model that represents the state of a system over time using a set of state variables and a set of dynamic equations [33]. In the context of microgrid deterioration, the State-Space model can be used to represent the state of the microgrid components over time, where the state variables are defined by the level of degradation or deterioration of each component [34][35]. The dynamic equations can be derived from physical or engineering principles, and the model can be used to predict the future state of the microgrid components and the expected failure rate over time.

The State-Space model is a complex failure rate model, requiring a high level of mathematical sophistication to understand and implement. This model uses a system of mathematical equations to describe the behavior of a system over time, and involves both continuous and discrete variables [36]. In terms of data requirements, the State-Space model requires a significant amount of data, including time-series data on the state of the system, as well as information on any inputs or external factors that may affect the system's behavior. Implementation of this model requires a good understanding of the system being modeled, as well as experience in developing and solving complex mathematical equations.

In terms of data extensiveness, the State-Space model is highly comprehensive, requiring a significant amount of data to accurately model the behavior of a system. This model considers both the current state of the system, as well as any inputs or external factors that may affect its behavior over time. The level of accuracy of the results produced by the State-Space model is high, as it is capable of capturing the dynamic behavior of a system over time. Moreover, the State-Space model is requiring a significant amount of data to produce accurate and comprehensive results.

3.8 Power Degradation Model

The Power Degradation Model is a statistical model that is used to describe the decline in power output of a photovoltaic (PV) module over time. In the context of microgrid deterioration, the Power Degradation Model can be used to estimate the rate at which the power output of a PV module declines over time, taking into account factors such as age, environmental factors, and usage history [37][38].

The Power Degradation Model can also be used to estimate the remaining useful life of a energy storage unit, which can be valuable information for maintenance planning and replacement decision making. Figure 7 shows an example of degradation model on battery SOC on various power degradation model derivative [39].

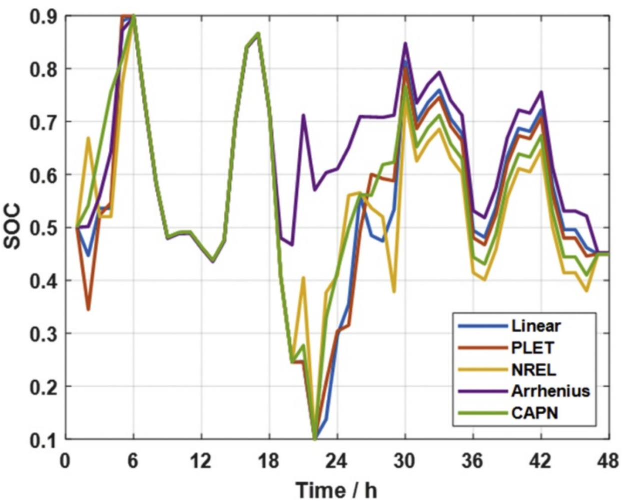

Figure 7. Example of battery SOC of various degradation models [39].

The Power Degradation Model is a type of failure rate model that predicts the decline of power output of a device over time. The mathematical sophistication of this model varies depending on the specifics of the implementation, but in general, it requires knowledge of regression analysis and statistical modeling. The amount and type of data required for the Power Degradation Model typically include detailed performance measurements taken over time, such as voltage, current, temperature, and power output.

In terms of data extensiveness, the Power Degradation Model requires a large amount of performance data, which should be comprehensive and accurately recorded in order to achieve reliable results. The level of accuracy of the results will depend on the quality and amount of data used, as well as the sophistication of the statistical models employed. The comprehensiveness of the results will depend on the scope of the analysis, which could include factors such as temperature, voltage, current, and other relevant parameters. The level of extensiveness of this model will depend on the amount of data and the comprehensiveness of the analysis.

3.9 Other models

The following models have been recognized as having the capability to express the failure rate within the microgrid domain. Despite this recognition, the available data and literature on these models is limited, resulting in a lack of in-depth information and descriptions. As a result, the descriptions of these models in the current literature are brief and only provide a basic overview.

Exponential failure rate model: The exponential failure rate model is a simple statistical model that assumes that the rate of failure for a product is constant over time. It requires limited mathematical sophistication, but the model's assumptions may not always hold in real-world applications [40].

Constant failure rate model: The constant failure rate model is a simple model that assumes that the rate of failure for a product is constant over time. This model requires limited mathematical sophistication and data, making it easy to implement. However, the results may not be accurate for all cases [41].

Power law model: The power law model is a statistical model that assumes that the rate of failure for a product is proportional to a power of time, more commonly called life decay model. This model requires moderate mathematical sophistication and may require more data compared to simpler models [42].

Log-normal distribution-based model: The log-normal distribution-based model is a more complex statistical model that assumes that the logarithm of the failure time for a product follows a normal distribution based on probability of the lifetime estimation. This model requires a higher level of mathematical sophistication and may require more data compared to simpler models [43].

Logistic regression model: The logistic regression model is a statistical model that uses a set of independent variables to predict the probability of a binary outcome (such as failure or success). This model requires a high level of mathematical sophistication and a large amount of data to be effective [44].

Accelerated life testing model: The accelerated life testing model is a complex statistical model that uses accelerated testing conditions to estimate the lifetime of a product. This model requires a high level of mathematical sophistication and may require a limited amount of data [45].

4. DISCUSSIONS ON COMPLEXITY AND EXTENSIVENESS LEVEL

This section provides comprehensive evaluations of the complexity and extensiveness of the dozen failure rate models analyzed in this study. This evaluation includes an analysis of the four levels of model complexity and data extensiveness as described in the methodology section. Table 1 resumes all models in regards with their level and domains. This section also examines the implications of these study for the design and implementation of rural microgrid systems, as well as for policy makers and stakeholders involved in the development and operation.

4.1 Evaluation of the Model Complexity

The level of mathematical sophistication required for a model can depend on the complexity of the data and the underlying system being modeled, and the choice of model should be based on the goals and limitations of the specific study or analysis.

Simple Level: This level of failure rate model is characterized by its simplicity and ease of use. It typically involves basic statistical concepts such as mean time between failures (MTBF) and is often based on empirical data and past experiences. These models can be used as a quick and straightforward way to estimate the failure rate of a system.

Intermediate Level: This level of failure rate model is characterized by its moderate complexity, incorporating a wider range of factors such as environmental conditions, system age, and component usage patterns. These models may use more advanced statistical methods, such as Weibull or Bathtub curves, to estimate the failure rate of a system.

Advanced Level: This level of failure rate model is characterized by its high level of complexity and mathematical sophistication. It often incorporates physics-based or engineering models to simulate the behavior of individual components and the system as a whole. These models can provide detailed insights into the failure mechanisms and the impact of different factors on the overall failure rate.

Expert Level: This level of failure rate model is the most complex and sophisticated, often requiring specialized knowledge and expertise in the relevant field. It may involve the use of advanced simulation techniques, such as Monte Carlo or Markov Chain analysis, to estimate the failure rate of a system. These models can provide a high level of accuracy and detail but may also require significant computational resources and time to run.

4.2 Evaluation of the Data Extensiveness

The level of data extensiveness for a failure rate model will depend on the accuracy and reliability desired from the model. The more accurate the model, the more data it will typically require, and the more specialized the data management and processing techniques will need to be.

Basic Extensiveness: These models are usually basic in nature and may use a limited amount of data. They may rely on assumptions and rough estimates to make predictions. These models are typically quick and easy to implement and require limited data collection and management. They are best suited for preliminary assessments of system performance or for simple systems where data availability is limited.

Intermediate Extensiveness: These models are more complex and require more detailed data to make predictions. They may use historical performance data, such as component failure rates or system performance metrics, to make more accurate predictions. The data required for these models may require specialized data collection and management techniques. These models are best suited for systems where more data is available, and for organizations that have a moderate level of experience with data analysis and management.

Advanced Extensiveness: These models are highly complex and require vast amounts of data to make precise predictions. They may use real-time data, such as system performance metrics and component failure data, to make highly accurate predictions. These models require specialized data collection and management tools and techniques to process the large amount of data. They are best suited for organizations with extensive experience in

Table 1. The level of complexity and extensiveness of recognized failure rate models

Failure Rate Models	**Domain Allocation***	**Level of Model Complexity**	**Level of Data Extensiveness**	**Ref.**
The Bathtub Curves	PV & CP	Intermediate	Advance	[8][9][10][11]
Weibull Distribution	PV, BT, CP, & DS	Intermediate	Advance	[12][13][15][16]
Markov Chain Model	PV, CP, TR, & DS	Expert	Expert	[17][18][19][20]
Battery State of Health (SOH) model	BT	Simple	Basic	[12][21][22][23]
Time-to-Failure (TTF) model	BT, CP, & TR	Intermediate	Intermediate	[24][25][26][27]
Arrhenius Equation Model	PV, BT, & CP	Simple	Basic	[29][30][31][32]
State-Space model	BT, CP, TR & DS	Advanced	Expert	[33][34][35][36]
Power Degradation Model	PV, BT, TR & DS	Advanced	Advanced	[37][38][39]
Exponential Failure Rate Model	BT & CP	Advanced	Intermediate	[40]
Constant Failure Rate Model	CP & DS	Simple	Basic	[41]
Power Law Model	BT & TR	Intermediate	Intermediate	[42]
Log-normal Distribution-based Model	TR & DS	Advanced	Intermediate	[43]
Logistic Regression Model	TR & DS	Advanced	Advanced	[44]
Accelerated Life Testing Model	BT & CP	Advanced	Intermediate	[45]

**PV: generation section, BT: storage units, CP: component layer, TR: transmission line, and DS: distribution network* data analysis and management, and for systems where a high level of accuracy is desired.

Expert Extensiveness: These models are highly specialized and require vast amounts of data, as well as specialized data analysis techniques, to make highly accurate predictions. They may also require specialized data management and processing infrastructure to handle the large amount of data. These models are best suited for organizations with extensive experience in data analysis and management, and for systems where a high level of accuracy is critical.

5. IMPLICATIONS OF THE LEVELS FOR RESEARCH, MANAGEMENT, AND POLICY

The categorizing of model complexity and data extensiveness, as presented in Table 1, can provide a clearer understanding of the advantages of these models when presented in an operational framework, such as Figure 8. This framework serves as a valuable tool for engineers in their design and development research, helps operators in managing the operation and maintenance of their microgrid site, and provides important insights for stakeholders in making informed decisions on funding and policy.

5.1 Implication for microgrid engineers

Categorizing the failure rate models into different levels based on mathematical sophistication, ease of implementation, data requirements, and accuracy provides engineers with a better understanding of the different models available and the trade-offs between their strengths and limitations.

Better understanding of the different models: Engineers can use the categorization to better understand the different models and the factors that make them unique. Moreover,

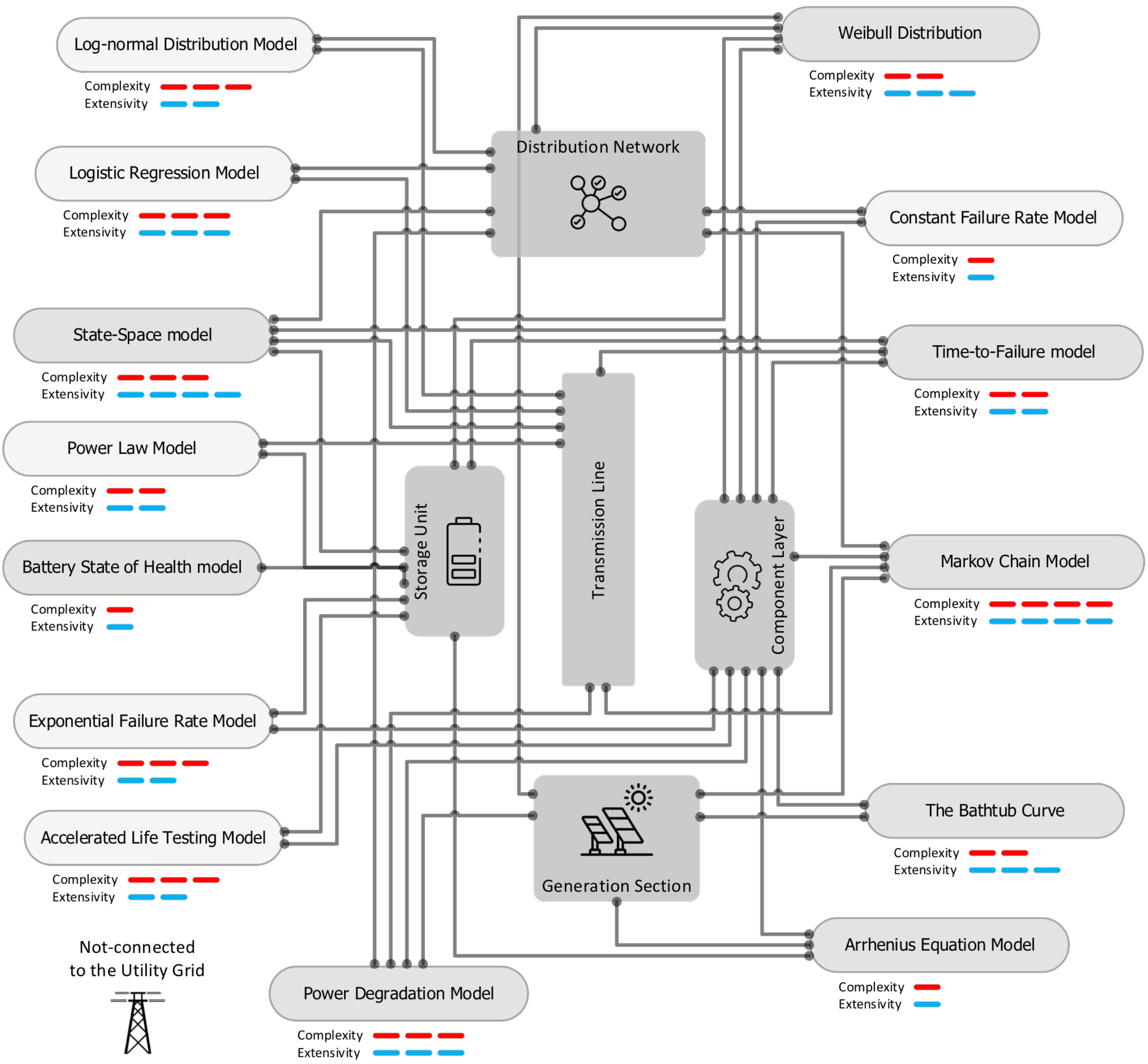

Figure 8. Implementation framework of the failure rate models into the rural microgrid domains

selecting the appropriate model: Engineers can use the categorization to select the most appropriate model for their specific needs, taking into account the resources and expertise available. For example, if an engineer is working on a project with limited resources, they may choose a model with low mathematical sophistication and ease of implementation, such as a constant failure rate model.

Furthermore, engineers can improve the project outcomes and enhancing project efficiency. For example, by selecting the most appropriate model, engineers can ensure that their projects have the best chance of success and deliver the desired outcomes. For example, in a renewable energy project, engineers may use a model with high accuracy, such as a dual exponential failure rate model or a log-normal distribution-based model, to predict the lifetime of the components and optimize the design for maximum efficiency. This results in a more reliable and efficient system that performs better and lasts longer, leading to a more successful project outcome. Additionally, the use of a model with lower mathematical sophistication and ease of implementation can improve the efficiency of the project by reducing the time and resources required to implement it.

5.2 Implication for microgrid operators

Categorizing the failure rate models into different levels provides microgrid operators with a better understanding of the models available and the trade-offs between their strengths and limitations. Operators with a better understanding of the different models can classify each failure factors that make them unique. Moreover, microgrid operators can use the categorization to select the most appropriate model for their specific needs, taking into account the resources and expertise available. For example, if a microgrid operator has limited resources and expertise, they may choose a model with low mathematical sophistication and ease of implementation, such as a constant failure rate model.

Similar with the benefits to the engineer, by selecting the most appropriate model, microgrid operators can ensure that their microgrid systems are operating at their best and delivering the desired operational schedule and maintenance roadmap. Microgrid operators can also save time and resources, improving the efficiency of their microgrid systems after knowing the potential failure ahead.

5.3 Implication for policy makers or stakeholder

By having a clear understanding of the strengths and limitations of different models, policy makers can make informed decisions about which models are best suited for their specific needs especially for future funding. For example, policy makers can use this information to prioritize funding for several hard-choice research that will help to improve the accuracy and usefulness of the models. Furthermore, it will in turn can help creating better policies for the implementation of a characterized rural microgrid systems.

Additionally, by funding research in the areas where further improvement is needed, policy makers can drive the development of advanced and more accurate models, ensuring that their policies are based on the best available data analysis and observed evidence. This can help to optimize the use of resources and improve the effectiveness and sustainability of prioritized rural microgrid systems. Moreover, by encouraging the development of user-friendly and accessible models, policy makers can increase the adoption of these systems and help to bring reliable and sustainable energy access to more people.

6. CONCLUSION

This study was to evaluate various failure rate models for deterioration in rural microgrids, and compare them based on their complexity and extensiveness. A comprehensive review of more than a dozen models was conducted, and each model was categorized into one of four levels of complexity and four levels of data extensiveness. The results of this study showed that there is a wide range of models available, with varying levels of complexity and data requirements. In terms of complexity, some models are relatively simple and easy to implement, while others are more advanced and require a higher level of mathematical sophistication. In terms of data extensiveness, some models require a large amount of data to be accurate, while others can be implemented with minimal data inputs. The results of this study potentially have significant implications for the design and implementation of rural microgrid systems. By understanding the complexity and data requirements of various failure rate models, policy makers and engineers can make informed decisions about which models are best suited for their particular needs. Additionally, the findings of this study can inform future research in this area, and help to guide the development of new and improved failure rate models for rural microgrids. Future research in this area should focus on developing new and improved models that can address the unique challenges of certain rural microgrids, and further advance the field of microgrid research and development.

ACKNOWLEDGEMENT

The authors would like to thank Badan Riset dan Inovasi Nasional (BRIN) and Universiti Teknologi Malaysia (UTM) for facilitating all the data collection and providing sophisticated literature on the completion of this work. The author would also like to thank all the UTM lecturers, BRIN researchers, staffs, and students who helps the accomplishment of this study.

This work was conducted as a part of Universiti Teknologi Malaysia (UTM) and Badan Riset Inovasi Nasional, Indonesia (BRIN) Collaborative Research Grant vot R.J130000.7351.4B734.

REFERENCES

[1] E. S. Jones, O. M. Akeyo, K. Waters, and D. M. Ionel, “Electric Power System Studies for a Multi-MW PV Farm and Large Rural Community with Net Zero Energy and Microgrid Capabilities,” in *2020 IEEE Industry Applications Society Annual Meeting*, Oct. 2020, pp. 1–4. doi:

10.1109/IAS44978.2020.9334740.

[2] A. G. Li and M. Preindl, “Assessing Degradation-Aware Model Predictive Control for Energy Management of a Grid-Connected PV-Battery Microgrid,” in *2022 IEEE Transportation Electrification Conference & Expo (ITEC)*, Jun. 2022, pp. 546–551. doi: 10.1109/ITEC53557.2022.9813768.

[3] A. Nawaz, J. Wu, J. Ye, Y. Dong, and C. Long, “Distributed MPC-based energy scheduling for islanded multi-microgrid considering battery degradation and cyclic life deterioration,” *Appl. Energy*, vol. 329, p. 120168, Jan. 2023, doi: 10.1016/j.apenergy.2022.120168.

[4] T. D. Atmaja *et al.*, “Component degradation and system deterioration: An overview of early termination of PV-DG microgrid system,” *J. Mechatronics, Electr. Power, Veh. Technol.*, vol. 13, no. 2, pp. 201–213, Dec. 2022, doi: 10.14203/j.mev.2022.v13.201-213.

[5] A. Nargeszar, A. Ghaedi, M. Nafar, and M. Simab, “Reliability evaluation of the renewable energy-based microgrids considering resource variation,” *IET Renew. Power Gener.*, vol. 17, no. 3, pp. 507–527, Feb. 2023, doi: 10.1049/rpg2.12611.

[6] K. T. Meselhy, H. A. Elmaraghy, and W. H. Elmaraghy, “Comprehensive Complexity-Based Failure Modeling for Maintainability and Serviceability,” *Proc. 1st CIRP Ind. Prod. Syst. Conf.*, no. April, p. 89, 2009.

[7] S. Roy, C. Asavathiratham, B. C. Lesieutre, and G. C. Verghese, “Network models: growth, dynamics, and failure,” in *Proceedings of the 34th Annual Hawaii International Conference on System Sciences*, pp. 728–737. doi: 10.1109/HICSS.2001.926276.

[8] Fengjun Yi, Chunjuan Jia, Weixing Zhang, Xiao Yang, and Pei Zhang, “Simulation of HVDC transmission system failure rate bathtub curve based on Weibull distribution,” in *2015 IEEE 2nd International Future Energy Electronics Conference (IFEEC)*, Nov. 2015, pp. 1–5. doi: 10.1109/IFEEC.2015.7361599.

[9] B. von Roedern, “On differences between bathtub curves and linear degradation describing PV module degradation,” in *Proceedings Volume 8825, Reliability of Photovoltaic Cells, Modules, Components, and Systems VI*, Sep. 2013, p. 88250C. doi: 10.1117/12.2024378.

[10] D. J. Wilkins, “The Bathtub Curve and Product Failure Behavior Part Two - Normal Life and Wear-Out,” *Reliability HotWire*, 2002. [Online]. Available: https://www.weibull.com/hotwire/issue22/hottopics22.htm

[11] D. J. Wilkins, “The Bathtub Curve and Product Failure Behavior Part One - The Bathtub Curve, Infant Mortality and Burn-in,” *Reliability HotWire*, 2002. [Online]. Available: https://www.weibull.com/hotwire/issue21/index.htm

[12] Q. Zhao *et al.*, “Research on State of Health for the Series Battery Module Based on the Weibull Distribution,” *J. Electrochem. Soc.*, vol. 169, no. 2, p. 020523, Feb. 2022, doi: 10.1149/1945-7111/ac4f21.

[13] O. M. Kam, S. Noël, H. Ramenah, P. Kasser, and C. Tanougast, “Comparative Weibull distribution methods for reliable global solar irradiance assessment in France areas,” *Renew. Energy*, vol. 165, pp. 194–210, Mar. 2021, doi: 10.1016/j.renene.2020.10.151.

[14] M. U. Afzaal *et al.*, “Probabilistic Generation Model of Solar Irradiance for Grid Connected Photovoltaic Systems Using Weibull Distribution,” *Sustainability*, vol. 12, no. 6, p. 2241, Mar. 2020, doi: 10.3390/su12062241.

[15] Mathworks, “Weibull Distribution : Compute Weibull Distribution pdf,” *Mathworks Help Center*, 2022. https://www.mathworks.com/help/stats/weibull-distribution.html#mw_e9866498-0076-4734-a73e-c1f8d7186d44

[16] E. O. Amuta, S. T. Wara, A. F. Agbetuyi, and B. A. Sawyerr, “Weibull distribution-based analysis for reliability assessment of an isolated power micro-grid system,” *Mater. Today Proc.*, vol. 65, pp. 2215–2220, 2022, doi: 10.1016/j.matpr.2022.06.244.

[17] W. Kim, H. Eom, and Y. Kwon, “Optimal Design of Photovoltaic Connected Energy Storage System Using Markov Chain Models,” *Sustainability*, vol. 13, no. 7, p. 3837, Mar. 2021, doi: 10.3390/su13073837.

[18] S. Miao, G. Ning, Y. Gu, J. Yan, and B. Ma, “Markov Chain model for solar farm generation and its application to generation performance evaluation,” *J. Clean. Prod.*, vol. 186, pp. 905–917, Jun. 2018, doi: 10.1016/j.jclepro.2018.03.173.

[19] S. Singh, S. Abdullah, N. A. Nik Mohamed, and M. S. Mohd Noorani, “Markov chain modelling of reliability analysis and prediction under mixed mode loading,” *Chinese J. Mech. Eng.*, vol. 28, no. 2, pp. 307–314, Mar. 2015, doi: 10.3901/CJME.2015.0112.012.

[20] A. Mamman, N. Baydoun, M. Sulaiman, and I. Ismail, “Globalization and its consequences: Malaysian managerial perspectives and implications,” *Asia Pacific Bus. Rev.*, vol. 19, no. 1, pp. 102–128, 2013, doi: 10.1080/13602381.2011.606648.

[21] P. V. H. Seger, R. Rigo-Mariani, P.-X. Thivel, and D. Riu, “A storage degradation model of Li-ion batteries to integrate ageing effects in the optimal management and design of an isolated microgrid,” *Appl. Energy*, vol. 333, p. 120584, Mar. 2023, doi: 10.1016/j.apenergy.2022.120584.

[22] S. Chen, J. Li, C. Jiang, and W. Xiao, “Optimal Energy-Storage Configuration for Microgrids Based on SOH Estimation and Deep Q-Network,” *Entropy*, vol. 24, no. 5, p. 630, Apr. 2022, doi: 10.3390/e24050630.

[23] I. Jorge, T. Mesbahi, A. Samet, and R. Boné, “Time Series Feature extraction for Lithium-Ion batteries State-Of-Health prediction,” *J. Energy Storage*, vol. 59, p. 106436, Mar. 2023, doi: 10.1016/j.est.2022.106436.

[24] J. W. McPherson, *Reliability Physics and Engineering*. Boston, MA: Springer US, 2010. doi:

10.1007/978-1-4419-6348-2.

[25] H. Allahyari, S. Haddadi, and A. A. Razi-Kazemi, "Reliability Analysis and Failure Mode Effects of a Modular Multilevel Pulse Generator," in *2022 13th Power Electronics, Drive Systems, and Technologies Conference (PEDSTC)*, Feb. 2022, pp. 65–70. doi: 10.1109/PEDSTC53976.2022.9767401.

[26] G. Asha and U. N. Nair, "Reliability properties of mean time to failure in age replacement models," *Int. J. Reliab. Qual. Saf. Eng.*, vol. 17, no. 01, pp. 15–26, Feb. 2010, doi: 10.1142/S0218539310003640.

[27] H. Abunima, J. Teh, and H. J. Jabir, "A New Solar Radiation Model for a Power System Reliability Study," *IEEE Access*, vol. 7, pp. 64758–64766, 2019, doi: 10.1109/ACCESS.2019.2916168.

[28] U. M. Damo, C. G. Ozoegwu, C. Ogbonnaya, and C. Maduabuchi, "Effects of light, heat and relative humidity on the accelerated testing of photovoltaic degradation using Arrhenius model," *Sol. Energy*, vol. 250, pp. 335–346, Jan. 2023, doi: 10.1016/j.solener.2023.01.002.

[29] A. Sinha, S. Pore, A. Balasubramaniyan, and G. TamizhMani, "Acceleration Factor Modeling for Degradation Rate Prediction of Photovoltaic Encapsulant Discoloration," in *2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC) (A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC)*, Jun. 2018, pp. 1342–1346. doi: 10.1109/PVSC.2018.8547944.

[30] O. Kittaneh, "On the Theory of the Arrhenius-Normal Model with Applications to the Life Distribution of Lithium-Ion Batteries," *Batteries*, vol. 9, no. 1, p. 55, Jan. 2023, doi: 10.3390/batteries9010055.

[31] T. Sun, B. Xu, Y. Cui, X. Feng, X. Han, and Y. Zheng, "A sequential capacity estimation for the lithium-ion batteries combining incremental capacity curve and discrete Arrhenius fading model," *J. Power Sources*, vol. 484, p. 229248, Feb. 2021, doi: 10.1016/j.jpowsour.2020.229248.

[32] A. Sinha *et al.*, "Prediction of Climate-Specific Degradation Rate for Photovoltaic Encapsulant Discoloration," *IEEE J. Photovoltaics*, vol. 10, no. 4, pp. 1093–1101, Jul. 2020, doi: 10.1109/JPHOTOV.2020.2989182.

[33] A. Solanki, A. Nasiri, B. Novakovic, and V. Bhavaraju, "State space modeling and stability assessment for a microgrid," *2015 IEEE Energy Convers. Congr. Expo. ECCE 2015*, pp. 533–538, 2015, doi: 10.1109/ECCE.2015.7309735.

[34] M. Noroozi, F. Haghjoo, H. Javadi, and M. Reza Zolghadri, "Power quality improvement in single-phase transformerless semi-quasi-Z-source inverters for off-grid photovoltaic systems," *Int. J. Electr. Power Energy Syst.*, vol. 145, p. 108703, Feb. 2023, doi: 10.1016/j.ijepes.2022.108703.

[35] K. Sakthivel, R. Krishnasamy, K. Balasubramanian, V. Krishnakumar, and M. Ganesan, "Averaged state space modeling and the applicability of the series Compensated Buck-Boost converter for harvesting solar Photo Voltaic energy," *Sustain. Energy Technol. Assessments*, vol. 53, p. 102611, Oct. 2022, doi: 10.1016/j.seta.2022.102611.

[36] E. I. Batzelis, G. Anagnostou, I. R. Cole, T. R. Betts, and B. C. Pal, "A State-Space Dynamic Model for Photovoltaic Systems With Full Ancillary Services Support," *IEEE Trans. Sustain. Energy*, vol. 10, no. 3, pp. 1399–1409, Jul. 2019, doi: 10.1109/TSTE.2018.2880082.

[37] G. Badran and M. Dhimish, "Field study on the severity of photovoltaic potential induced degradation," *Sci. Rep.*, vol. 12, no. 1, p. 22094, Dec. 2022, doi: 10.1038/s41598-022-26310-y.

[38] J. Kim, M. Rabelo, S. P. Padi, H. Yousuf, E.-C. Cho, and J. Yi, "A Review of the Degradation of Photovoltaic Modules for Life Expectancy," *Energies*, vol. 14, no. 14, p. 4278, Jul. 2021, doi: 10.3390/en14144278.

[39] S. Wang *et al.*, "Impact of battery degradation models on energy management of a grid-connected DC microgrid," *Energy*, vol. 207, p. 118228, Sep. 2020, doi: 10.1016/j.energy.2020.118228.

[40] R. Shehla and A. A. Khan, "Reliability analysis using an exponential power model with bathtub-shaped failure rate function: a Bayes study," *Springerplus*, vol. 5, no. 1, p. 1076, Dec. 2016, doi: 10.1186/s40064-016-2722-3.

[41] J. B. Bowles, "Commentary - caution: constant failure-rate models may be hazardous to your design," *IEEE Trans. Reliab.*, vol. 51, no. 3, pp. 375–377, Sep. 2002, doi: 10.1109/TR.2002.801850.

[42] N. Yan, X. Li, and Y. Zhong, "Life decay characteristics identification method of retired power batteries based on inverse power law model of accelerated life test," *Energy Reports*, vol. 8, pp. 950–956, Aug. 2022, doi: 10.1016/j.egyr.2022.02.120.

[43] S. Ammach, M. A. Majid, and O. A. Kittaneh, "Estimating the Lifetime Model for The Commercial Concentrator III-V Triple-Junction Solar Cells Using The Lognormal Distribution," in *2021 6th Asia Conference on Power and Electrical Engineering (ACPEE)*, Apr. 2021, pp. 751–755. doi: 10.1109/ACPEE51499.2021.9437043.

[44] T. Liu, S. Wang, S. Wu, J. Ma, and Y. Lu, "Predication of wireless communication failure in grid metering automation system based on logistic regression model," in *2014 China International Conference on Electricity Distribution (CICED)*, Sep. 2014, pp. 894–897. doi: 10.1109/CICED.2014.6991837.

[45] W. Gu, Z. Sun, X. Wei, and H. Dai, "A new method of accelerated life testing based on the Grey System Theory for a model-based lithium-ion battery life evaluation system," *J. Power Sources*, vol. 267, pp. 366–379, Dec. 2014, doi: 10.1016/j.jpowsour.2014.05.103.