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Battery Energy Storage Capacity Estimation for Microgrids Using Digital Twin Concept

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Abstract: Globally, renewable energy-based power generation is experiencing exponential growth due to concerns over the environmental impacts of traditional power generation methods. Microgrids (MGs) are commonly employed to integrate renewable sources due to their distributed nature, with batteries often used to compensate for power fluctuations caused by the intermittency of renewable energy sources. However, sudden fluctuations in the power supply can negatively impact battery performance, making it challenging to select an appropriate battery energy storage system (BESS) at the design stage of an MG. The cycle count of a battery in relation to battery stress is a useful measure for determining the general health of a battery and can aid in BESS selection. An accurate digital replica of an MG is required to determine the required cycle count and stress levels of a BESS. The Digital Twin (DT) concept can be used to replicate the dynamics of the MG in a virtual environment, allowing for the estimation of required cycle numbers and applied stress levels to a BESS. This paper presents a Microgrid Digital Twin (MGDT) model that can estimate the required cycle count and stress levels of a BESS without considering any unique battery type. Based on the results, designers can select an appropriate BESS for the MG, and the MGDT can also be used to roughly estimate the health of the currently operating BESS, allowing for cost-effective predictive maintenance scheduling for MGs.

Keywords: digital twin; battery energy storage health monitoring; microgrid digital twin

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1. Introduction

A digital twin (DT) is a digital representation of a physical item or assembly using integrated simulations and service data. The digital representation holds information from multiple sources across the product life cycle. This information is continuously updated and is visualized in a variety of ways to predict current and future conditions in both design and operational environments to enhance decision-making [1]. DT enables designers and operators to investigate real systems' behaviors in a simulation environment, providing several unique advantages, including the following:

- Designers can make informed decisions by observing the true dynamics of a system in a virtual environment;
- Maintenance schedules can be effectively planned;
- Modifications and upgrades can be safely verified using DT before integrating them into the actual system;
- System performance can be evaluated without disturbing the real system.
- DT enhances financial decision-making capabilities;
- Operational costs can be significantly reduced by using remote monitoring.

The concept of DT was initially used in NASA's Apollo missions, where they mimicked the conditions on the main vehicle in space in an identical vehicle located on the Earth which was called the "twin" [2]. However, the term DT was officially introduced in 2012 by NASA in their integrated technology roadmaps. NASA defines DT as an integrated multi-physics, multi-scale simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and so on to mirror the life of its corresponding flying twin [3].

Currently, DTs are vastly employed in different industries such as the manufacturing, automotive, healthcare, and power industries with the advancement of the fourth industrial revolution that is based on Cyber-Physical Systems (CPS), Information and Communication Technologies (ICT), and Internet-of-Things (IoT) [4]. The aforementioned technologies fulfill the major requirements to execute DTs. In this manuscript and research, our focus industry is electrical power generation.

Applications of Microgrids (MGs) are rapidly increasing due to the utilization of distributed small-scale renewable power sources. Furthermore, according to the U.S. Energy Information Administration (EIA), there is expected to have a 56% global increase in energy demand by 2040 due to the rapid acceleration of industrialization and urbanization [5]. However, legacy AC power grids are not capable of following the same growth rate as per the increasing demand. As a result, it is predicted to have a huge growth rate of MG integrations in power networks. It is estimated to have an 11.3% compound annual growth rate (CAGR) in the MG market from 2021 to 2031 [6]. The concept of DT has found numerous applications in multidisciplinary areas, such as manufacturing facilities and building complexes, with the emergence of Industry 4.0 [6].

The introduction of DT technology in MGs creates unique benefits for consumers and designers. From the perspective of consumers, DT boosts the reliability and availability of the MGs. For designers, DT allows for optimizing and evaluating designs in a low-risk and low-cost platform. Therefore, DT uplifts the performances of MGs, starting from the planning stage to the operational, maintenance, and expanding stages [7].

In the current context of MGs, Distributed Renewable Energy Sources (DRES) such as solar, wind, and wave energy are being widely integrated as power sources to reduce the carbon footprint for power generation [8]. Worldwide policies have been introduced to promote the generation of green power using DRES, and due to their distributed nature, MGs are widely used to integrate these DRES into power generation [9,10]. However, the intermittent nature of DRES requires Battery Energy Storage Systems (BESS) to maintain the supply–demand balance in MGs. To maintain supply–demand stability, BESS is required to absorb and release power depending on the power generation variations of the DERS and load variations. Each battery has a lifetime that can be measured as the cycle life of the battery. Additionally, the rate of change of the power of the battery applies stress to the battery in each cycle. Each battery manufacturer specifies a specific cycle count and safe stress level. Therefore, knowing the required cycle count and stress levels at the design stage allows designers to select a suitable BESS for their MGs.

Furthermore, exposure to sudden power supply variations causes gradual loss of relevant properties of the components, which is known as degradation. As a result, periodic maintenance is a mandatory requirement for prolonging the lifespan of these systems that are exposed to sudden power variations. In terms of maintenance, two types of maintenance scheduling practices are commonly employed at the industrial level: predictive and preventive maintenance. Table 1 illustrates the characteristics of these maintenance schemes.

Table 1. Predictive maintenance vs. Preventive maintenance.

Feature	Predictive Maintenance	Preventive Maintenance
Purpose	• Performed to mitigate predicted failures.	• Perform to prevent unexpected failures.
Frequency	• Not on a regular basis. • Maintenance visits only occur when potential failures are identified.	• On a regular basis. • Maintenance visits are not scheduled, considering the system's performance.
Cost	• Low due to lower number of visits.	• High due to higher number of visits.
Complexity	• High.	• Low.

In summary, the intermittent nature of DRES poses challenges for designing and operating MGs. When designing MGs, selecting the appropriate BESS is crucial to meet the MGs' requirements. During operation, MGs require close monitoring and preventive maintenance to sustain operational conditions, leading to high operational costs. Despite their promising benefits, challenges in designing and high operational costs limit the integration of MGs, particularly in harsh environments such as remote areas, polar latitudes, and offshore facilities.

As shown in Figure 1, the DT of an MG creates an exact virtual replica of an actual MG in a digital world where operators can access the required parameters and operating conditions without visiting the physical MG. Microgrid Digital Twin (MGDT) can provide accurate forecast data for designers to select the required BESS for the particular MG and for operators to plan future operational activities such as maintenance, dispatching generators, etc. Therefore, in terms of maintenance, operators can schedule predictive maintenance instead of regular preventive maintenance, which lowers the number of maintenance visits required. Predictive maintenance reduces the downtime of the MG and reduces operational costs due to fewer maintenance visits required.

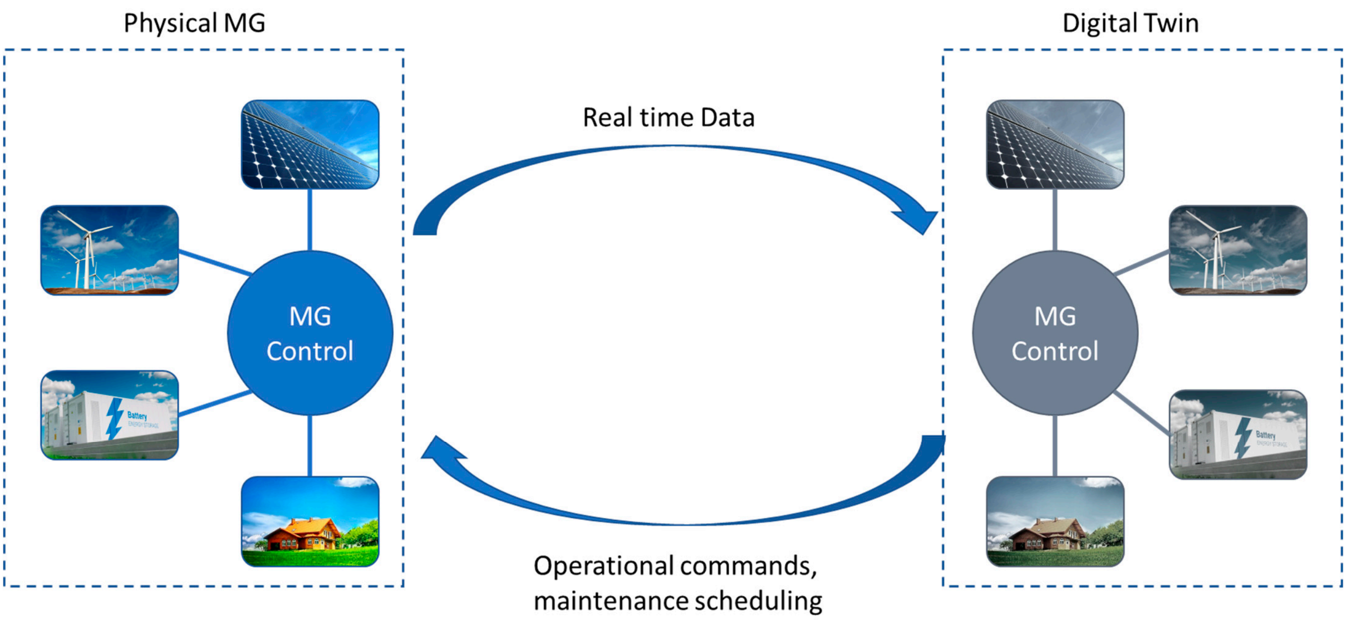

Figure 1. MGDT Concept.

BESS plays a crucial role in managing the supply and demand balance in MGs. However, the operational cost of a BESS is high due to the need for frequent maintenance. The MGDT enables operators to access real-time parameters of the MG remotely, which can be used to assess the health of the BESS. This paper proposes a method for estimating the health of the BESS in MGs using DT concepts. The proposed method can primarily aid designers in planning microgrids during the initial stages and future expansion stages. Additionally, it can assist operators in scheduling maintenance. The paper is structured as follows: Section 2 provides details of BESS used in MGs, Section 3 details the DT applications in MGs, Section 4 describes BESS health monitoring, Section 5 outlines the design methodology, Section 6 presents the results and discussion, and finally, Section 7 concludes the work.

2. Battery Energy Storage Systems in MGs

BESS is a commonly employed energy storage mechanism in MGs, mainly for two reasons:

1. To maintain the system stability by compensating for the sudden voltage variations caused by renewable energy sources;
2. To increase the revenue by storing energy during low-tariff periods.

Table 2 represents a summary of battery types commonly used as BESS in MGs.

Table 2. Comparison of commonly used battery technologies in MGs.

Type	Advantages	Disadvantages	Reference
Lead-Acid Battery	• High efficiency (70–80%) • High cell voltage • Low cost • High energy density • Long calendar life (5 to 15 years)	• Short cycle life (500–2000 cycles) • Low specific energy • Periodic maintenance is required. • Premature failures may occur due to sulphation. • Environmental effects caused by lead	[11–14]
Lithium-Ion (Li-ion) Battery	• High volumetric and gravimetric energy density • High efficiency (>90%) • Rapid response time (in milliseconds) • Low self-discharging rate (5% per month)	• Low cycle depth of discharge (DoD) • High cost of Lithium, Cobalt, and Nickel • Electrical abuse • Thermal runaway may be caused by exposure to elevated temperatures	[14–19]
Sodium-Sulfur (NaS) Battery Storage Systems	• High discharging time (6–7 h) • High cycle life (more than 4500 cycles) • Longer battery calendar life (usually upwards to 10 years) • High power density • High efficiency (up to 90%) • Fast response time during charging and discharging (in milliseconds)	• Operating temperature is between 3000–3500 °C • Low practicality • Very high operating cost • High risk	[20–24]
Redox Flow Battery	• High reliability	• High complexity • High maintenance cost	[11,25,26]

Generally, batteries have a response time in the range of milliseconds, which allows them to compensate for sudden fluctuations caused by DRES. Such rapid variations in power flow cannot be captured using single-period time optimization methods, such as power flow techniques [27]. However, there are multi-period power flow techniques available in the literature with higher accuracy compared to single-period time optimization methods [28]. Despite this, even these approaches are unable to dynamically capture the power flow and degradation characteristics of BESS.

Battery degradation is mainly divided into two categories: calendar ageing and cycling ageing. Calendar ageing is associated with the fading of battery capacity while stored without use, and cycling ageing is primarily dependent on the charging and discharging rates. Cycle ageing is also affected by temperature and depth of discharge (DoD) [29]. In terms of evaluating the battery health of an operational BESS, cycle ageing is a more crucial factor compared to calendar ageing. There are many battery degradation models available in the literature, which can be divided into two categories: theoretical and empirical models [30]. Theoretical models are developed based on the chemical degradation mechanisms of batteries, taking into account their operating conditions. Improving the accuracy of these models requires modelling at the molecular level, making the models more complex [31]. Empirical models are based on experimental data where battery terminal voltage is represented as a function of the state of the charge and the current. In [32], empirical models are classified into three types: shepherd models, Unnewehr models, and Nernst models. Each empirical model is a tailormade degradation model for a specific BESS based on stochastic charging and discharging patterns [33]. Therefore, empirical models are highly unique to the application as a result, and single empirical models cannot be employed in multiple applications.

3. Microgid Digital Twin (MGDT)

MGDT creates an exact virtual replica of an actual MG, allowing designers to investigate the actual system performance in a range of operating conditions, from normal operation to extreme events. MGDT can be used in different phases, such as the design phase, operational phase, and future expansion phase, and provides valuable input for operational decision-making in each phase.

Most components of the MG, with the exception of batteries, do not require regular maintenance. The lifespan of the MG is primarily determined by the BESS, which has the shortest lifespan of all components. Therefore, selecting an appropriate BESS during the design phase is critical. The MGDT can capture the necessary information for selecting a suitable BESS for a specific MG. Once the requirements are established, the appropriate BESS can be chosen to meet the needs of the system.

Additionally, it is crucial to maintain the operational conditions of the BESS. Therefore, regular preventive maintenance is typically conducted. However, maintenance costs can significantly impact revenue. To minimize operational costs, predictive maintenance can be performed instead of preventive maintenance. The MGDT can assist operators in scheduling predictive maintenance.

Given that MGs are often situated in remote geographical locations, it is necessary to have remote monitoring facilities to assess the requirements and operating conditions of the MG without the need for physical visits. With the advancement of Industry 4.0, communication technologies in industries have greatly improved, leading many industries to develop MGDTs to take advantage of their unique benefits.

The accuracy of MGDTs is generally proportional to the number of parameters measured. However, measuring a high number of parameters requires a large number of sensors and high bandwidth data transfer capabilities, which increases the cost of MGDTs. Therefore, designers need to carefully select the minimum number of inputs required for the MGDT to accurately capture the true dynamics of the MG for a particular task while reducing the cost. In this study, we developed an MGDT model that uses minimal real-time parameter monitoring to achieve two objectives:

1. Capturing the necessary information to assist designers in selecting appropriate battery energy storage systems (BESS) for microgrids during the design and expansion stages;
2. Assisting operators in scheduling maintenance for operational microgrids.

3.1. DCMG Case Study

Figure 2 represents the simple DCMG model used in the study. The DC MG model consists of a single solar panel, a battery, and a DC load. Key technical details of the solar panel are tabled in Table 3 [34].

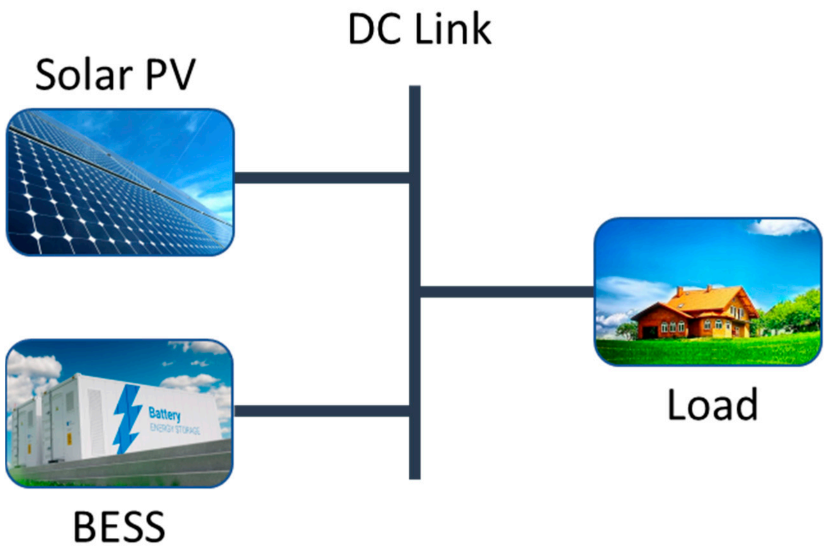

Figure 2. DC MG used in the study.

Table 3. Solar cell technical details.

Detail	Parameter	Units
Model	TP660P	
Maximum Power output	275	W
Cell type	Poly Crystalline	
Cell Dimensions	156 × 156	mm
Number of cells	60	
Operating Voltage	31.7	V
Open-Circuit Voltage	38.7	V
Operating Current	8.69	A
Short-Circuit Current	9.17	A
Module efficiency	16.9	%

Irradiance, power generation of the solar panel, and the load demand are the parameters that require continuous monitoring to update the status of MGDT.

In [35], a dataset is available for the aforementioned solar panel with irradiance and solar power output data. The performance of the MGDT is planned to evaluate using this data set. Irradiance is used as the input for the solar model to produce power as the output. Equation (1) is used to represent the relationship between power (P) and irradiance of a solar panel.

$$P = A \times r \times H \times PR \tag{1}$$

where H is the irradiance per square meter, A represents the area of the solar panel, and r, PR represent the solar panel yield constant and performance ratio, respectively. The performance ratio (PR) is a constant that falls within the range of 0.5 and 0.9. The panel yield constant (r) can be computed using Equation (2), and it is always less than or equal to 1.

$$r = \frac{Power\ of\ a\ one\ solar\ panel}{Area\ of\ a\ one\ panel} \tag{2}$$

The performance ratio of the solar panel (PR) and its yield constant (r) vary from panel to panel and depend on operating conditions. Additionally, these constants may vary due to degradation. Therefore, parameter estimation is employed to fine-tune the value of the performance ratio.

3.1.1. Load Profile of the MG

In this research, a variable DC load is utilized to simulate the load profile of a typical DC household. In order to match the power ratings of the solar panel, the actual household demand profile extracted from [36] is scaled down.

3.1.2. Battery Model

In the available literature, several DT models have been developed for batteries and BESS, as described in references [37–42]. These models can be broadly categorized as equivalent circuit-based or electrochemical-based models. The equivalent circuit-based models rely on the measurement of line parameters, whereas the electrochemical-based models are based on the measurement of physical parameters such as temperature. However, creating a DT model that accurately reflects the true dynamics of batteries necessitates a substantial amount of data. This, in turn, necessitates the use of a large number of sensors and high-bandwidth data transmission. As a result, developing a highly accurate DT model for a battery or BESS is a costly and complex undertaking.

The primary objective of this research is to develop an MGDT that can estimate the necessary characteristics of BESS to assist designers in both the initial planning and future extension stages. Accordingly, this study aims to create an MGDT that is not dependent on any particular BESS or battery technology.

Cycle count and stress levels are critical parameters that determine the lifespan and overall health of any BESS [43–45]. Since the BESS is used to compensate for supply–demand mismatches in MGs, examining the supply–demand match using the MGDT can determine the BESS charging and discharging profiles. By analyzing these profiles, this study can determine the cycle count and stress levels of the BESS. Based on this data, designers can select suitable BESS during the designing and future expansion stages. Furthermore, operators can obtain a rough understanding of the current operating condition of the BESS. However, it should be noted that this is just an estimation since an identical battery model is not used in this study.

This approach offers a more generalized and cost-effective means of estimating the necessary characteristics of the required BESS, allowing designers to choose a suitable BESS for MGs based on expected lifespan and maintenance requirements.

3.2. Period Parameter Fine Tuning

A key characteristic of a DT that distinguishes it from conventional simulation-based studies is its ability to interpret degrading properties. To accurately capture these properties, periodic parameter tuning is required. The performance ratio of the solar panel (PR) and its yield constant (r) are constants in a solar panel model that changes over time due to degradation. To replicate the conditions in the MGDT as in the MG, the performance ratio and its yield constant values must be periodically retuned.

MATLAB® and Simulink® served as the simulation platform for this study [46]. The parameter estimation tool available in Simulink enables the estimation of parameters based on actual data. Parameter estimation is an iterative process commonly used by engineers to develop accurate plant models for DTs. Similarly, the parameter estimation tool is employed in the proposed MGDT to estimate the aforementioned constant in the solar panel model.

4. Battery Health Monitoring

Once the solar irradiance data and the demand power are input into the DT, the battery power consumption ($P_{Battery}$) will be determined based on the supply–demand balancing in the MG as described in Equation (3).

$$P_{Battery} = P_{Solar} - P_{Load} \quad (3)$$

where P_{Solar} and P_{Load} represent the output power from the solar and load, respectively. The health of a battery is directly linked to the number of battery cycles and the corresponding stress levels of these cycles. These stress levels can be determined by monitoring the charging and discharging profile of the battery. The charging and discharging profile of a BESS is not a regular profile but rather a highly dynamic one. Therefore, it is crucial to identify cycles accurately from the charging and discharging profile, as this research is based on a cycle counting approach.

Level crossing counting, peak counting, simple range counting, and Rainflow counting are some of the commonly used cycle-based counting techniques. These methods are primarily used in the analysis of metal fatigue [30]. Among the aforementioned cycle-based techniques, the Rainflow cycle counting technique has the lowest relative error percentage, which is 11%, while other techniques have error percentages ranging from 19% to 27% [47]. The Rainflow cycle counting method is employed in this study, as it has been extensively utilized in material fatigue analysis [48,49], as well as in battery cycle counting applications [50,51]. The Rainflow counting method is a well-established technique for monitoring the health of Li-ion batteries [52,53]. Shi et al. [54] demonstrated the efficacy of the Rainflow algorithm in accurately identifying battery cycles in their study. Their study highlights the convex nature of the algorithm in capturing cycles within batteries.

Rainflow Cycle Counting

The Rainflow cycle counting method was introduced by Matsuishi and Endo in 1968 for use in fatigue analysis [55]. The Rainflow algorithm is based on the water flow pattern of a "pagoda" roof. Prior to executing the Rainflow algorithm, the peaks and valleys of a power profile must be identified. Once the peaks and valleys are established, the power profile is rotated 90 degrees clockwise. Each peak or valley is considered a source of water that drops down from the "Pagoda" roof. The cycle count is performed separately for peaks and valleys. A half-cycle is counted if one of the following conditions is met:

1. If the water flow terminates due to the end of the time series;
2. If the water flow terminates due to merging with another water flow that initiated in an earlier peak/valley;
3. If the water flow terminates due to a higher peak/valley.

The stress of a half cycle is calculated by taking the difference in powers between the starting and termination points of the water flow in each half cycle. Finally, half cycles with equal stress levels are combined to determine the complete number of cycles for each stress level.

5. Design Methodology

As shown in Figure 3, the DT of the solar panel is modelled based on Equation (1), where the solar irradiation data received from the actual MG is fed as input to the model. The model generates output power for each corresponding irradiance value. However, when the output power of the model is compared to the actual power output of the solar panel, it can be observed that the two profiles do not match, as shown in Figure 4. This is due to the solar panel yield constant (g) and performance ratio (k), which varies with degradation. To improve the accuracy of the model, parameter estimation is employed to tune those constants.

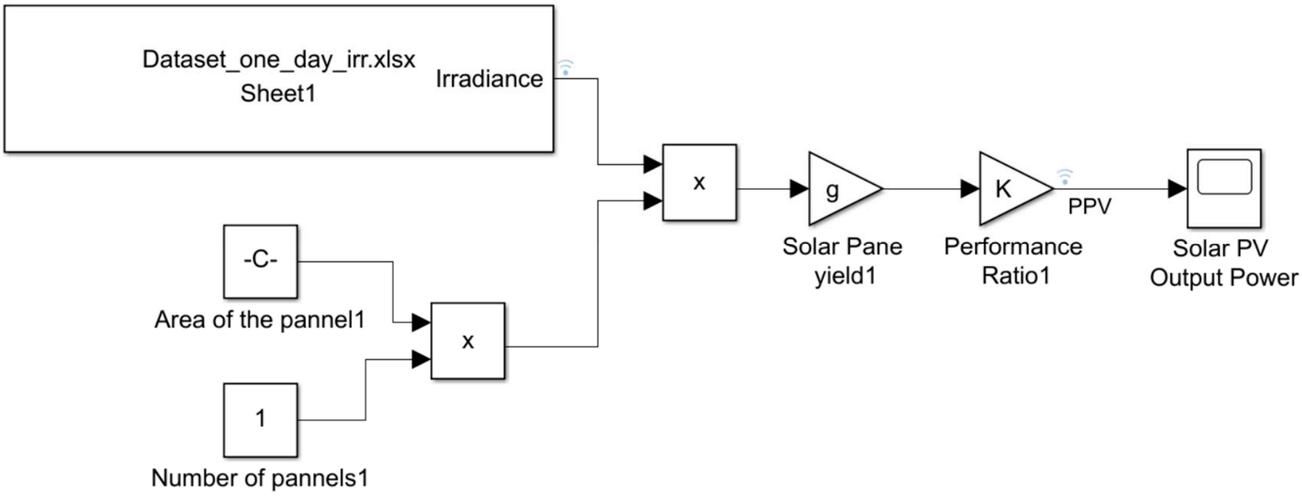

Figure 3. DT Solar panel model.

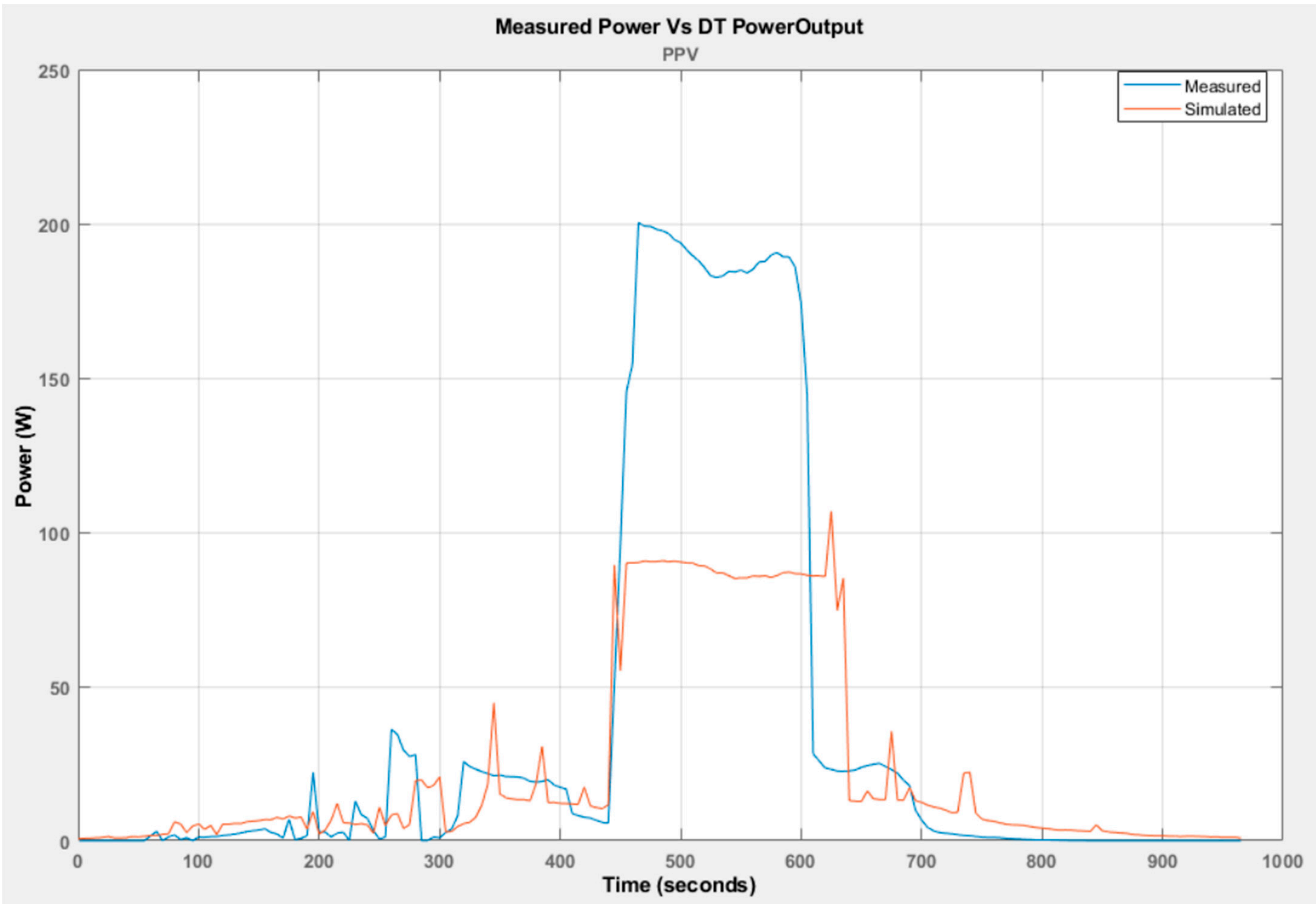

Figure 4. Measured and Simulated power outputs.

As depicted in Figure 5, the process of parameter estimation involves performing several iterations to obtain the values of the solar panel yield constant (g) and performance ratio (k). During each iteration, the simulated solar power output error is calculated by comparing it with the measured actual power output of the solar power system. Limitations for the variables (g and k) can be pre-defined ($0.5 \leq k \leq 0.9$ and $g \leq 1$). The MATLAB® parameter estimation tool employs a parameter selection approach to minimize the discrepancy between actual and simulated outputs. This involves identifying the suitable values for the variables within their specified limits. The parameter estimation process utilizes an objective function that calculates the error between the actual and simulated outputs, while the limitations of the variables serve as constraints for the error minimization function. By considering both the objective function and variable constraints, the parameter estimation tool is able to provide suitable values for the variables g and k within their designated ranges that produce the lowest error. Figure 6 shows the power output of the actual and simulation model of the solar panel for the same irradiance levels after parameter estimation. Thus, it is necessary to regularly fine-tune the DT to maintain an accurate representation of the MG.

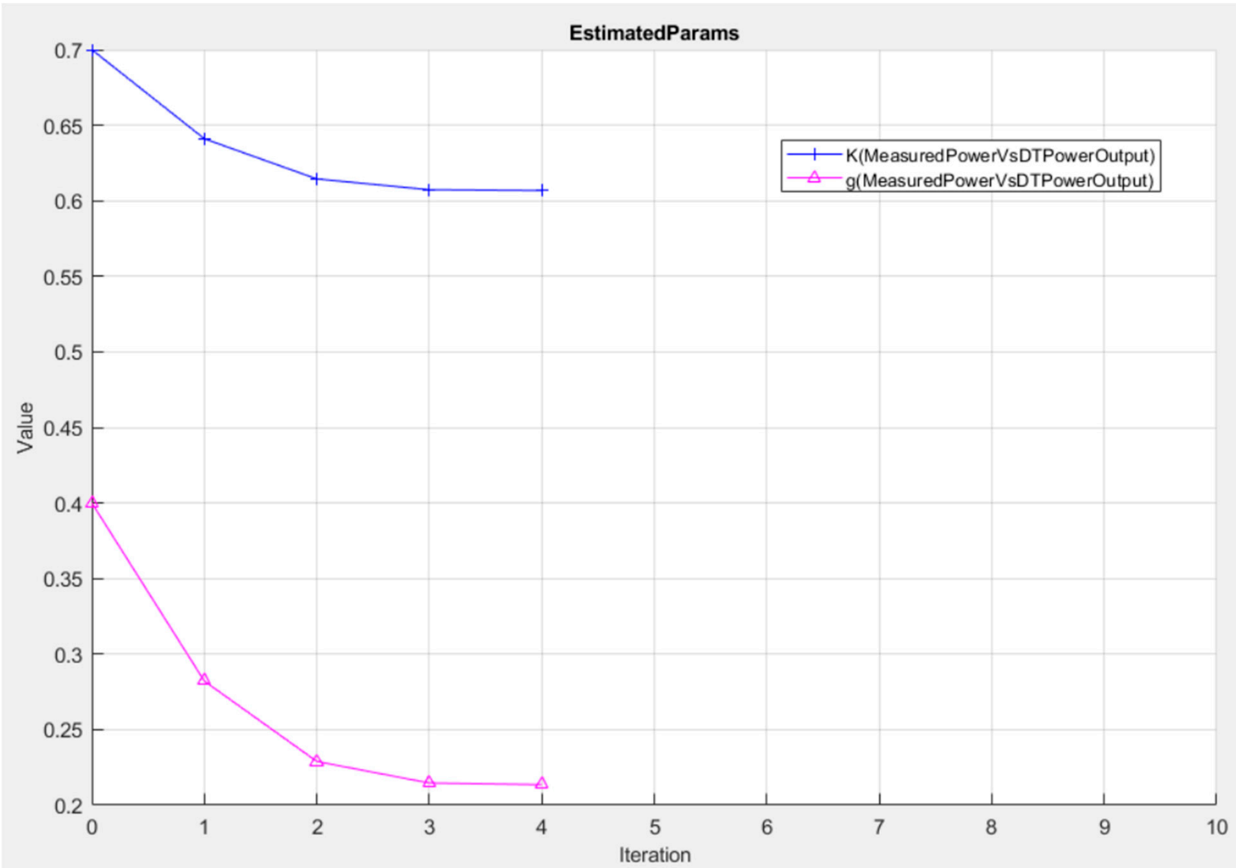

Figure 5. Parameter estimation.

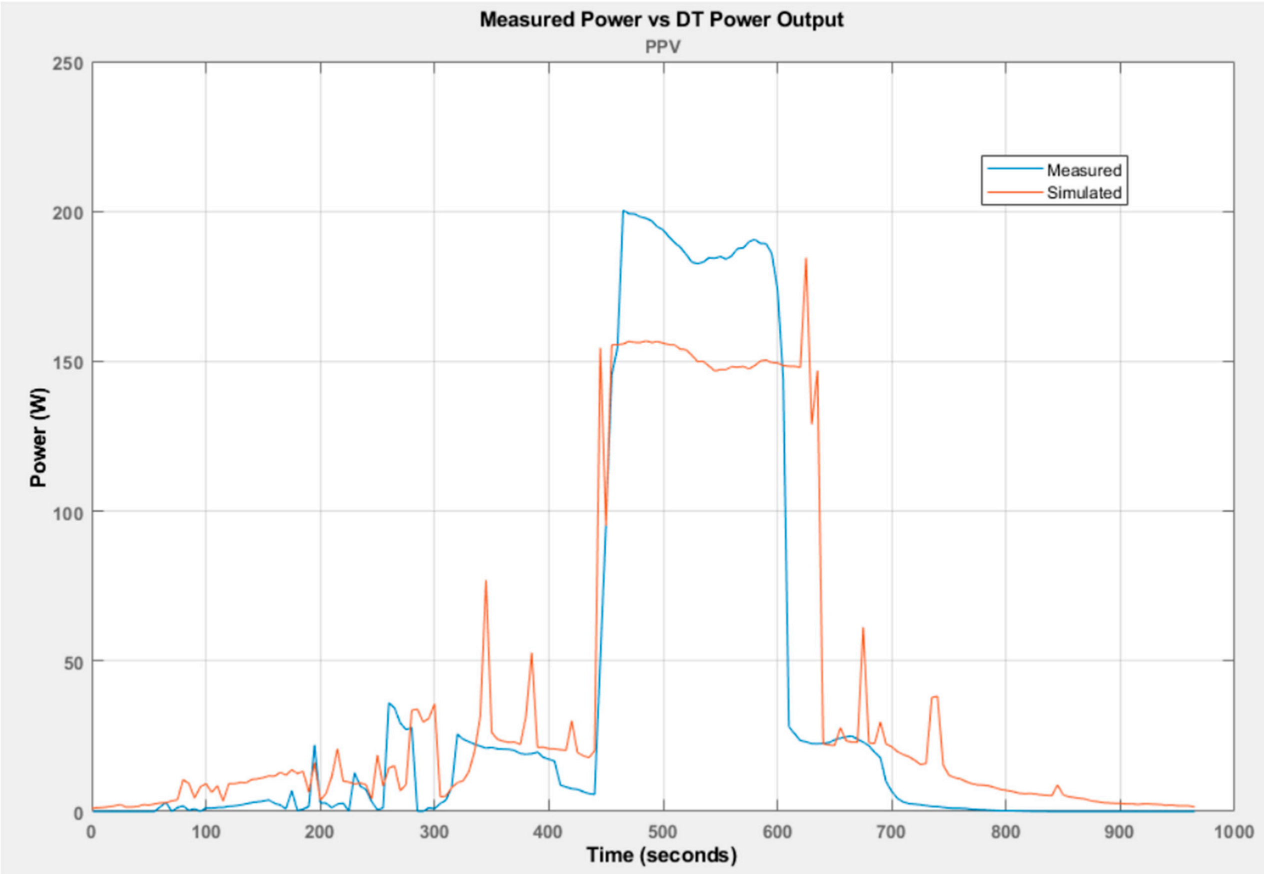

Figure 6. Measured and Simulation Power output after parameter estimation.

Figure 7 shows the Equation (3) model, which is used to calculate the power flow of the BESS. The load profile is updated with load data transmitted from the actual MG. Figure 8 illustrates the block diagram of the proposed system. The required inputs for the MGDT to generate the power profile of the BESS are the solar PV irradiation values, load profile, and measured PV power output. The solar PV DT model generates PV output based on the irradiation values. This output is then compared to the demand data from the load profile to calculate the required BESS power for maintaining the supply–demand match within the MG. Additionally, the power output error between the simulated and actual solar PV is calculated, and if the error exceeds the acceptable tolerance value, parameter estimation is performed to adjust the solar PV DT model. Figure 9 shows the power profile of the BESS generated from the MGDT model. Afterward, identifying the peaks and valleys of the BESS power profile is necessary to execute the rainflow algorithm. The "findpeak" function built into MATLAB® is utilized to identify peaks and valleys in the BESS power profile. This function identifies peaks by detecting data points that are greater than their two neighboring data points. Furthermore, this function is capable of detecting both positive and negative peaks within the data. Finally, the Rainflow algorithm is employed to count the cycles with respect to the stress levels. The study uses a sample rate of 100 Hz.

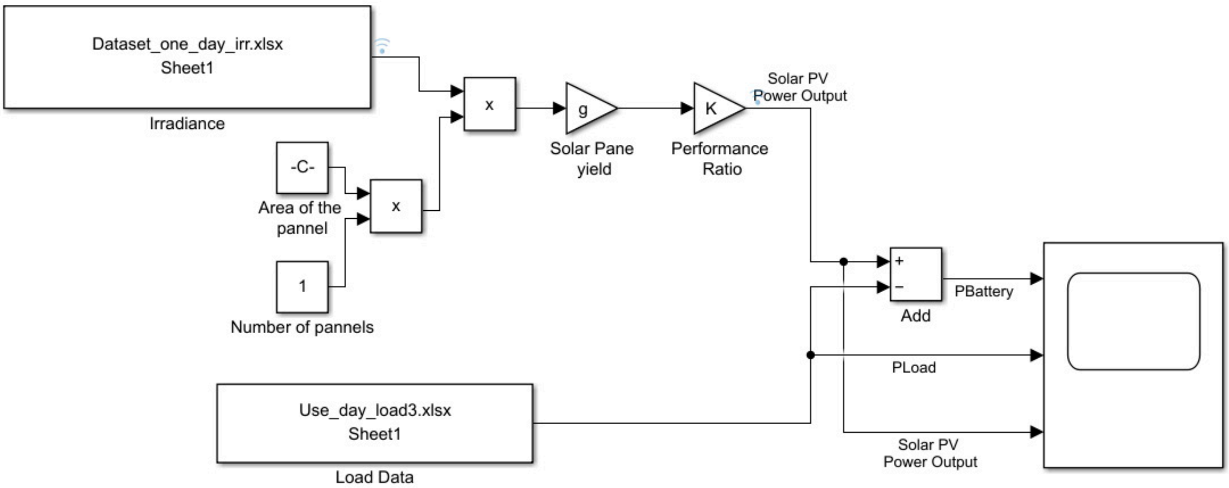

Figure 7. MGDT simulation model.

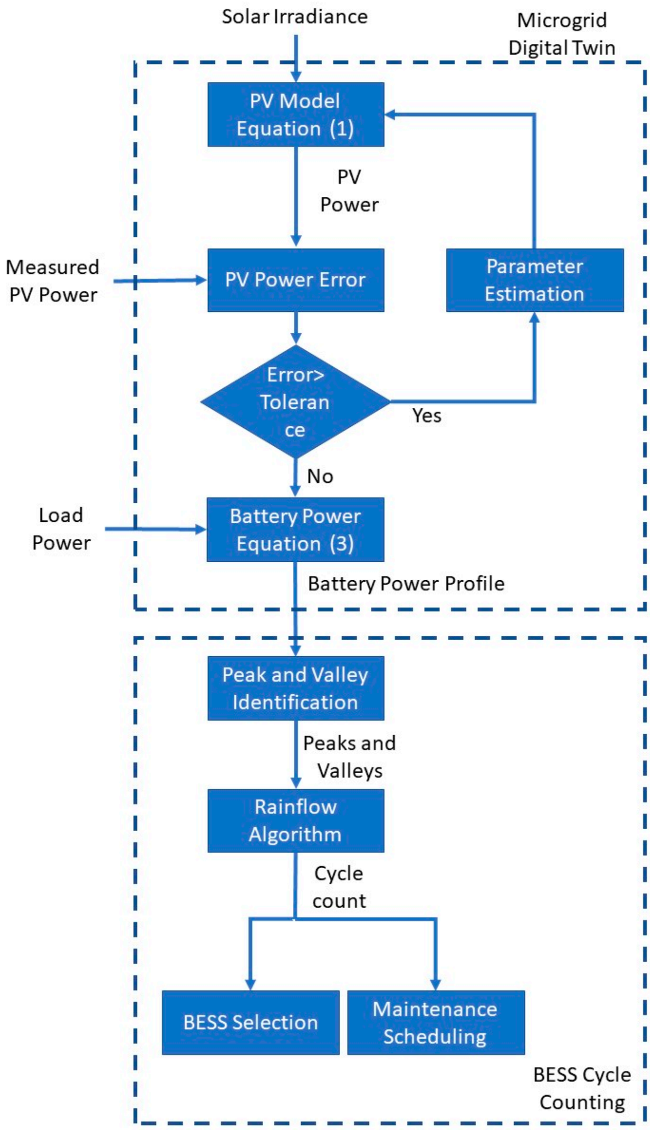

Figure 8. System block diagram.

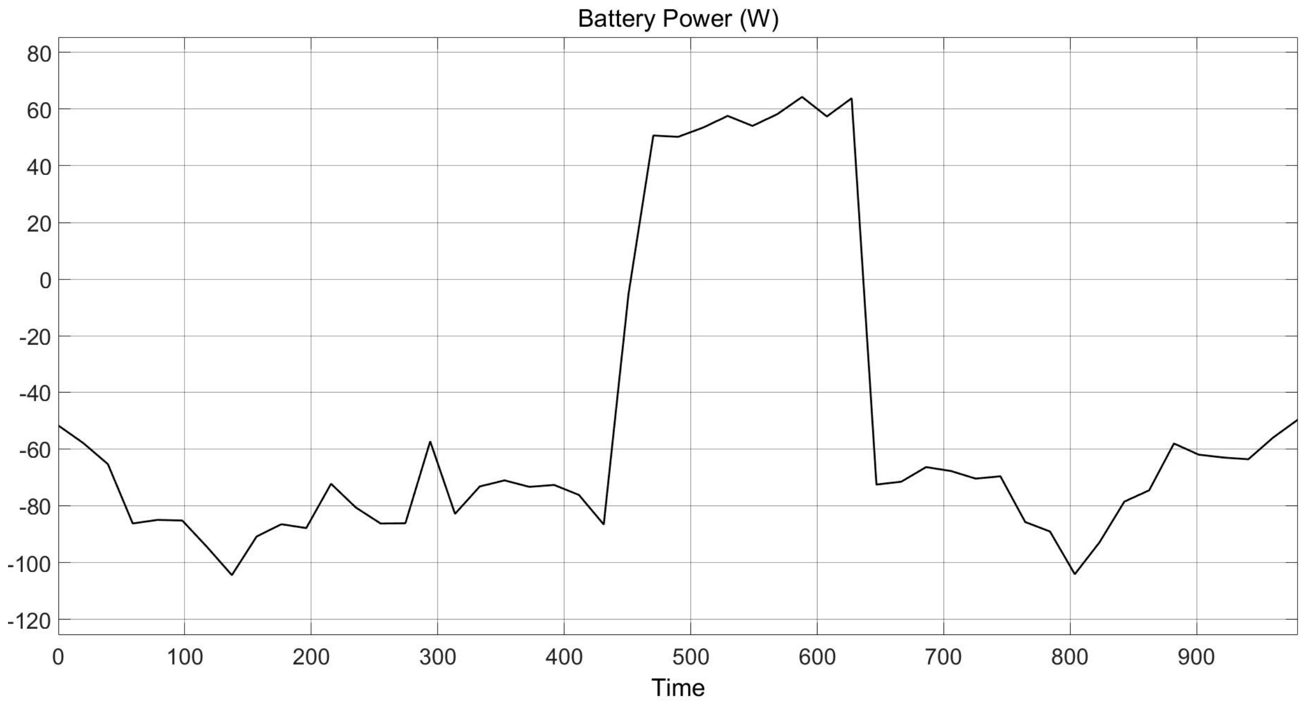

Figure 9. Power profile of the BESS.

As shown in Figure 8, by observing the cycle count and the stress levels of the required BESS, designers can accordingly select suitable types of BESS for particular MGs. Additionally, using the MGDT concept, operators can estimate the health of a BESS roughly based on cycle count and stress level data. There are established methods to determine the health of the BESS using the cycle count and the stress levels, such as [56–60]. However, the accuracy of BESS health estimation for an operational MG may be low due to the absence of the actual BESS model.

Data transmission between the actual MG and the DT is vital for the effective functioning of an MGDT. However, the proposed concept requires only the minimum amount of data transmission as the MGDT only needs three parameters: irradiance, solar PV output power, and power consumption by the loads. Among these parameters, irradiance and solar PV output are necessary for the continuous operation of the MGDT, while solar PV power output is required only for calibrating the solar PV model.

As a result, the proposed MGDT does not require high-bandwidth data transmission networks to operate. This concept reduces the need for expensive and high-capacity data transmission networks. However, it is important to note that the data transmission system aspects of the MGDT are not discussed in detail in this paper.

6. Results and Discussion

BESS are a critical component of MGs, helping to balance energy supply and demand and provide backup power in case of outages. However, it is important to accurately capture the performance of the BESS in order to ensure their longevity and effectiveness in the MG.

Figure 10 shows the critical peaks and valleys captured from the BESS power profile. It is crucial to accurately capture these peaks and valleys for the successful execution of the Rainflow algorithm. Figure 11 displays the output of the Rainflow algorithm, which plots the cycle counts in relation to the stress levels. The stress level, which represents the power difference between each cycle, is crucial in determining the life of the BESS. Higher stress levels significantly impact the health of the BESS, whereas lower stress levels have a minimal effect. These results can be used in various stages of MGs.

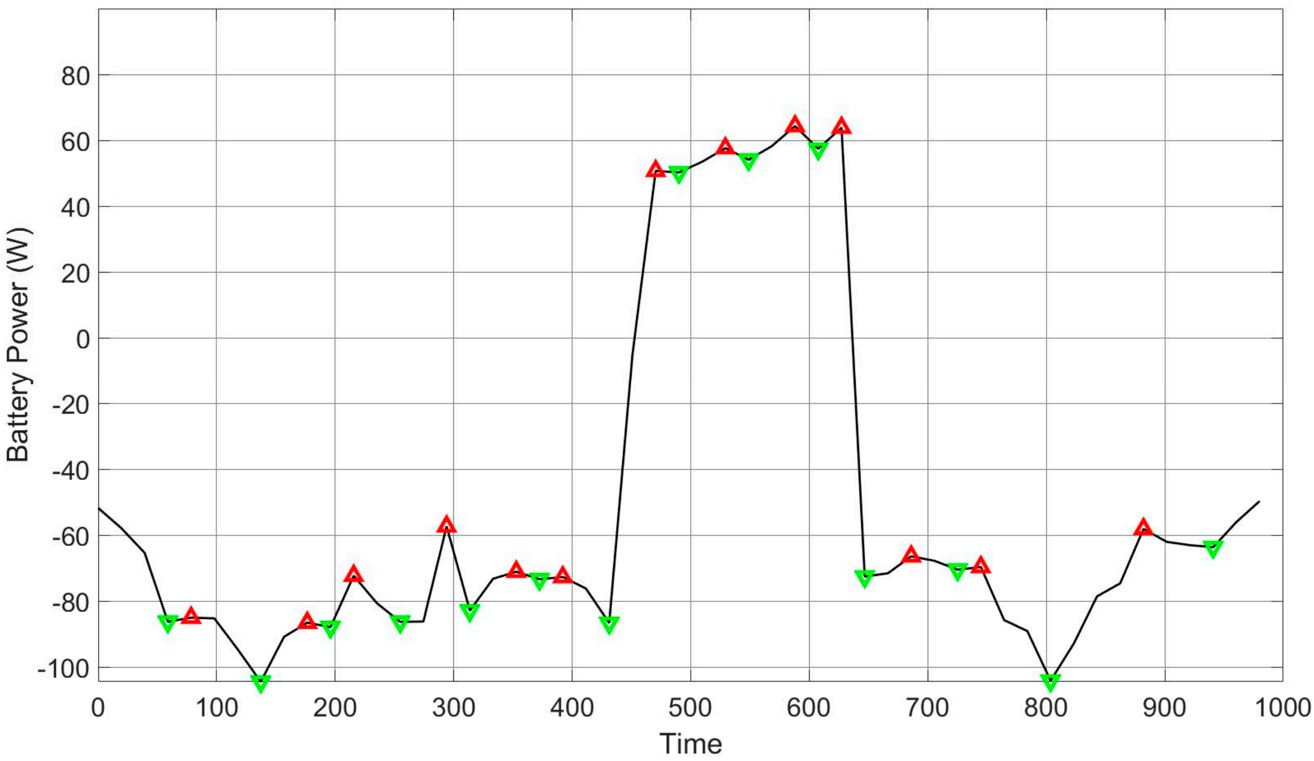

Figure 10. Critical Peaks (Red triangles) and valleys (Green triangles) captured from the BESS.

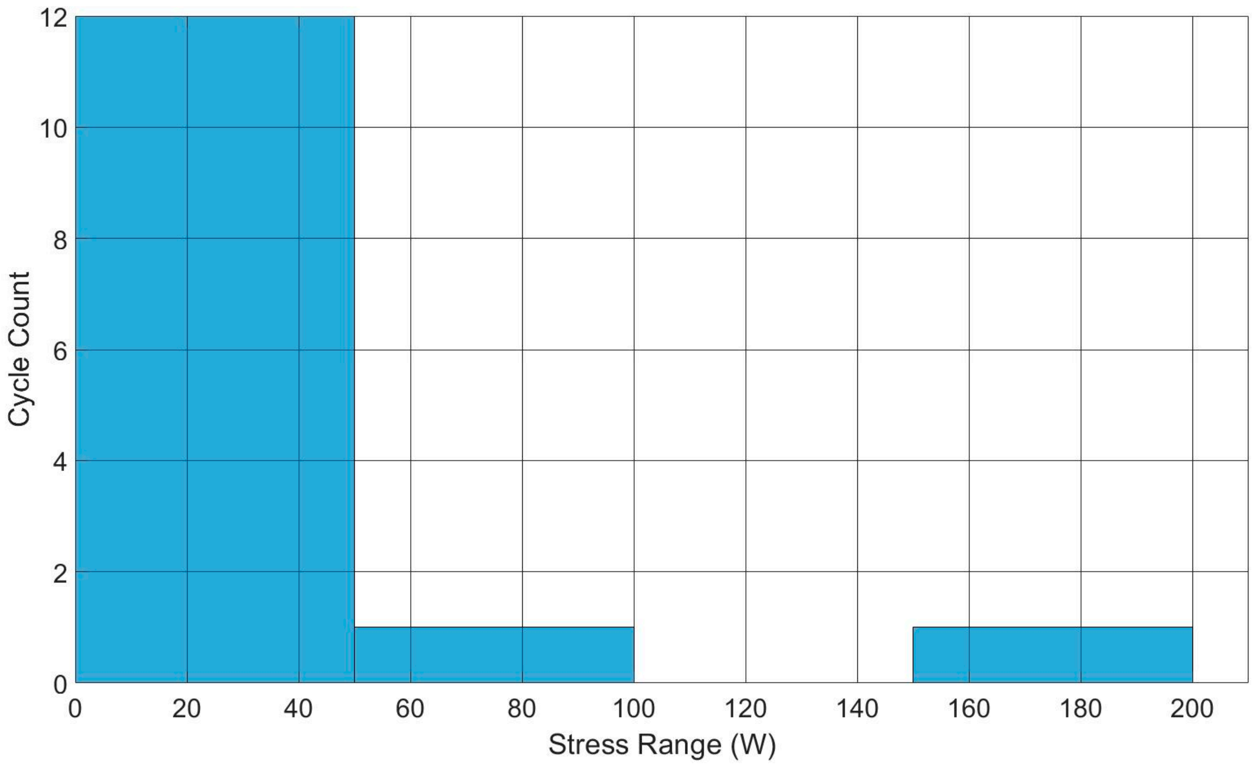

Figure 11. Cycle Count from the Rainflow algorithm.

The proposed MGDT requires only irradiation and load data as inputs, making it suitable for use in all major stages of management:

- It can be employed in the planning stage to select the appropriate BESS;
- It can be employed in the operation stage to schedule maintenance based on the BESS operation conditions;
- It can be employed in the decision-making process for future expansions.

During the planning stage, with the irradiance forecast and the demand profile forecast, MGDT can generate the cycle count vs. stress profile for the BESS. These characteristics are very useful for the designers when selecting a BESS for the MG.

For currently operational MGs, MGDT provides a measurement of the cycle count and the applied stress of the BESS. Operators can estimate the operation conditions of the BESS using the provided cycle count and stress data and schedule predictive maintenance to help extend the lifespan and ensure continued effectiveness in the MG. However, the accuracy of the model is limited due to the absence of an actual model of the currently used BESS.

MGDT can be used to aid decision-making in future expansions of existing MGs. By forecasting future demand and analyzing cycle count and stress level variations of current BESS, MGDT can predict the suitability of current BESS for future expansion. Additionally, MGDT can help in selecting new BESS for existing MGs, ensuring that the new BESS is capable of meeting the expected demand and stress levels.

Due to the fact that there is no requirement for a specific BESS model in this concept, it is more applicable during the design stage, where designers are required to select a BESS for MGs. Since the required cycle count and stress levels of a BESS are crucial parameters in the selection process, proposing the MGDT concept can be very useful for designers.

Furthermore, through parameter estimation, the MGDT can be fine-tuned to capture the actual dynamic behavior of the MG, which enhances the performance of the DT. Regular parameter fine-tuning is required to perform this parameter estimation, and with that, the degradation patterns of solar PV can also be identified. With identified degradation patterns, the DT can be modified to self-calibrate over time instead of relying on parameter tuning. This is not in the scope of this paper and is planned to be implemented in future stages.

The results of this study will help to ensure the long-term viability of BESS in PV-based energy systems. Furthermore, future stages of this research will integrate specific batteries and battery management systems into the MGDT. This integration will expand the limitations of the MGDT, providing more accurate modeling and simulation capabilities for PV energy systems that incorporate BESS. Ultimately, this will lead to more efficient and effective integration of BESS into the larger energy system, enabling greater use of renewable energy sources.

7. Conclusions

As discussed in the Results and Discussion section, the proposed MGDT model can be effectively applied in a wider range by using minimal and easily available data as inputs. Given that BESS plays a significant role in MGs, careful selection of the BESS is crucial. The proposed MGDT can estimate the BESS requirements for MGs during the initial planning stages and future expansion stages. Using forecast irradiance and demand data, the MGDT can predict the cycle count and stress levels of BESS, providing valuable support to designers in selecting the appropriate BESS for their design. Parameter tuning enables the solar PV DT model to accurately capture the true dynamics of the actual solar PV, enhancing the overall accuracy of the MGDT.

Moreover, operational costs in MGs are significantly affected by maintenance expenses. Hence, efficient management of maintenance expenses can boost revenue. Although most components in MGs do not necessitate frequent upkeep, regular maintenance is essential for BESS. Typically, MGs employ preventive-based routine maintenance schedules, which can be expensive. The proposed MGDT can offer cycle counts and corresponding stress levels to MG operators, enabling them to gauge the health of the BESS. Based on the estimated health, operators can schedule predictive maintenance. However, the lack of an exact BESS model in the MGDT limits the accuracy of the estimated health.

In summary, the proposed MGDT model is a valuable tool for designers to select appropriate BESS for both new and existing MGs. Moreover, it can assist operators in scheduling predictive maintenance for currently operating MGs.

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