**Review**

**An Overview on Electric-Stress Degradation Empirical Models for Electrochemical Devices in Smart Grids**

Martín Antonio Rodríguez Licea 1,*,†, Francisco Javier Pérez Pinal 2,† and Allan Giovanni Soriano Sánchez 1,†

1 CONACYT-Celaya Institute of Technology, Guanajuato 38010, Mexico; allan.soriano@itcelaya.edu.mx
2 Department of Electronics of the Celaya Institute of Technology, Guanajuato 38010, Mexico; francisco.perez@itcelaya.edu.mx
* Correspondence: martin.rodriguez@itcelaya.edu.mx
† These authors contributed equally to this work.

**Abstract:** The conversion from existing electrical networks into an all-renewable and environmentally friendly electrification scenario is insufficient to produce and distribute energy efficiently. Electrochemical devices’ premature degradation as a whole caused by electrical stressors in smart grids is incipient from an energy management strategies (EMS) perspective. Namely, few electrical-stress degradation models for photovoltaic panels, batteries, fuel cells, and super/ultra-capacitors (SCs), and particular stressors can be found in the literature. In this article, the basic operating principles for such devices, existing degradation models, and future research hints, including their incorporation in novel EMS, are condensed. The necessity of extending these studies to other stressors and devices is also emphasized. There are many other degradation models by non-electrical stressors, such as climatic conditions and mechanical wear. Although novel EMS should manage both electrical and non-electrical degradation mechanisms and include non-electrochemical devices, models with pure non-electrical-stressors are not the subject of this review since they already exist. Moreover, studies for the degradation of non-electrochemical devices by electrical stressors are very scarce.

**Keywords:** smart grid; degradation model; fuel cell; battery bank; photovoltaic panel; PV panel; supercapacitor; ultracapacitor

1. **Introduction**

From an electrical theory perspective, the first reported degradation model seems to date from the early 1960s, and it was intended primarily to determine how much electromagnetic interference deteriorated a radio signal below the ionosphere [1]. The model allowed the authors to predict the interference that will be experienced by a receiver located within a large deployment of transmitters and noise sources. In the same decade, the benefits of predicting the systematic degradation of materials, vacuum tubes, mechanical devices, germanium detectors, and even population projections on different scenarios inspired the notion of a stressor.

The concept of a stressor varies between disciplines. For instance, in [2] stressors are defined as any perturbations in the system or the environment that threaten to disrupt the organism’s optimal functioning. In this work, a stressor is understood as a measurable condition, stimulus, agent, or event that causes the degradation of a device’s specific properties or characteristics. Additionally, the literature shows that stress-based degradation models often provide more information than time-to-failure data to assess and predict systems’ reliability [3]. A general classification of degradation models is presented in Figure 1 (based on [4]), in which the model types for aimed for this work are highlighted in green.

On the other hand, the conversion of now obsolete electrical networks towards fully renewable smart grids is a clear example in which clean electricity is used more efficiently. The smart grid is a collection of diverse components, technologies, and disciplines, and energy management strategies (EMS) development is a crucial component to achieve a safe,
secure, and resilient electrical infrastructure [5]. Unfortunately, the high complexity of the smart grid’s premature-degradation mechanisms for one or more renewable/green power generators makes its controlled slowdown too complicated. Indeed, the precise estimation for a single power generating device is cumbersome, and it requires prolonged experimentation periods.

![Degradation Models](image)

**Figure 1.** Classification of degradation models in reliability analysis, based on the information presented in [4].

Nowadays, there is a tendency to generate EMS tolerant to failures and uncertainty. Still, it is also essential to detect and mitigate stressors to improve the smart grid’s longevity. Future modern and intelligent EMS must also consider diminishing the degradation by stressors of electrical and non-electrical nature. Some typical examples of electrical stressors that intelligent EMS can handle are power rate, ripple level, operating frequency, depth of discharge, current draw, current rate, and overloads, among others, depending on the power source device’s nature.

Hence, the knowledge about the leading electrical causes of degradation and their mechanisms during the interaction with other variables, such as temperature, humidity, and cycling, among others, is of high relevance. However, the recent development of strategies that consider the degradation of components is still nascent. Indeed, contemporary EMS consider only one or two types of clean energy generators in a systematic degradation scenario. For instance, in [6–8] the authors presented an optimization approach to avoid the premature degradation of a fuel cell integrated into vehicular microgrid scenarios (isolated smart grids). Additionally, in [9–14], the authors studied the mitigation of premature degradation of energy storage systems (battery systems) integrated into smart grids. Similarly, reviews performed up to now focus on a single power generator or collector. See [15] for batteries, references [16–18] for fuel cells, and [19,20] for photovoltaic modules.

Therefore, an essential requirement to estimate the remaining useful life is establishing their current state of degradation in practical applications utilizing models. Although precise and complex theoretic degradation models have been developed for some smart grid components, their accuracy depends on the availability, precision, and variability of its parameters, affecting their usage in real-time EMS. Novel EMS must calculate several degradation models simultaneously, and theoretical ones include complex nonlinear functions to be calculated in a real-time application (model-treatability problem).

We investigate relevant results focusing on mathematically tractable degradation models (both normal and accelerated physics-based) focused on smart grid components in this work. This investigation’s goal is to summarize for the first time the empirical or semi-empirical degradation models for electrochemical devices in smart grids instead of reliability, fully analytic, or artificial intelligence models. Consequently, the following contributions to the state of the art are now emphasized:
1. Empirical and semi-empirical models should be extended to consider stressors of electrical nature and include non-electrochemical devices.

2. Studies about the electrical-nature stressors on batteries, photovoltaic module/panels (PVMs), fuel cells, super/ultra-capacitors (SCs), and interconnected devices are needed. Indeed, many of the empirical models need validation experiments and in-depth analysis.

3. Combined degradation models can generate generalized smart grid models, but studies for determining major stressors are needed. This can help perform in-depth analyses on smart grid resilience and reliability, increasing confidence in this technology.

The paper is presented in sections as follows. Section 2 presents photovoltaic panel degradation; potential-induced and reverse current degradation phenomena are discussed. Batteries’ degradation is provided in Section 3; capacity-fade and power-fade degradation types and state of health are given. Section 4 is focused on fuel cells; catalysis surface, voltage oscillations, ohmic and activation overvoltage, and degradation rate are summarized. SC overvoltage degradation is provided in Section 5, followed by degradation on other devices in Section 6. Finally, additional areas of opportunity and conclusions of this work are detailed in Section 7.

2. Photovoltaic Panel Degradation

A photovoltaic module/panel (PVM) has an encapsulated matrix of solar cells connected in series or parallel. A front glass protects its components from contaminants that could alter its chemical composition. The simplified operating principle of a solar cell is as follows. Photons from solar irradiation hit the panel’s surface and are absorbed by semiconductor materials, such as silicon or gallium arsenide. The electrons of semiconductors, housed in orbitals of quantized energy, interact with photons freeing themselves from the atoms to which they were confined initially, producing an electron flux (See Figure 2).

![Figure 2. Illustration of a solar cell. A depletion layer separates two layers of semiconductor (doped) material (N and P, respectively). Base substrate and encapsulation layers are added at the bottom and top, respectively, and glass covers the cells/panel’s top. A metallic frame regularly covers the sides and bottom of a matrix of cells. The photons from solar light impact the N material, releasing electrons that flow through the voltmeter and fill the P material’s holes.](image-url)

According to manufacturers, a degraded PVM reaches less than 80% of its initial power for maximum (usable) irradiation. Non-electric degradation of PVMs is mainly related to environmental conditions. Some of the non-electrical stressors are well identified and include temperature, humidity, UV light, rapid light variation, and dust. For instance, dust accumulation can be characterized by its chemical, biological, electrostatic, and physical properties reducing and even permanently degrading the panel’s efficiency [20]. Pure
non-electrical degradation models are not the aim of this paper; the interested reader can review [19,21,22] and the references therein for further information.

On the other hand, degradation of PVMs by electrical stressors has been verified for the so-called potential induced degradation (PID). It is well known that PID combined with non-electric stressors, such as temperature and humidity, increases the degradation rate. Some researchers also included the reverse current as an electric degradation stressor and named the phenomenon reverse current degradation (RCD); regularly, external devices such as bypass diodes are installed to mitigate it. However, understanding of PID and the RCD is incomplete, and research shows that many non-electrical stressors influence degradation successions. In fact, different concepts and variants of the PID concept can be found in the literature. In the following, advances in the study of these phenomena are described. Table 1 describes the nomenclature for this section.

Table 1. Nomenclature for photovoltaic modules.

| Symbol | Description                           | Units |
|--------|--------------------------------------|-------|
| $P$    | Actual attainable power              | W     |
| $P_0$  | Rated power                          | W     |
| $R_{sh}$ | Shunt resistance                   | Ω     |
| $V_p$  | Frame voltage, respect to ground    | V     |

2.1. Potential Induced Degradation

The PID phenomenon is regularly associated with series arrays of two or more operative PVMs (string) because the total voltage is always greater than that of a single panel [23]. A potential between the PVMs’ cells and its metal-frame is created because all frames are connected to a common ground (safety concern). Then, a parasitic counter-current can flow through the front glass/encapsulation to the PVM’s cells (see Figure 3 for an illustration), producing irreversible and reversible damages (depending on its intensity and the PVM’s chemical design). Recent research has demonstrated that high humidity levels (and the correlated temperature) can increase these parasitic leakage currents by increasing the conductivity on the surface of the PVM, hence accelerating the PID’s rate [24].

Figure 3. A string of photovoltaic modules (PVMs). Since the PVMs’ frames are connected to the ground of the output voltage $V_T$ (blue wires), there are potentials $V_{p2}, \ldots, V_{pn}$ between negative poles (gray wires) of $PV_2, \ldots, PV_n$ and the ground. The highest frame potential is $V_{pn}$ and can be high enough to create a parasitic current flowing through the front glass and encapsulation of the PVM, degrading their solar cells. Although $PV_n$ is more predisposed to suffer this degradation because the potential is major, it can occur in any module from $PV_1$ to $PV_n$. Many authors know this degradation phenomenon as PID.
Although the PID risk can be minimized using different electrical connection topologies (non-series and isolated, among others), it is not always possible due to the high output voltages required and harsh environmental conditions, such as in large-scale solar farms. Hence, future research on EMS can be directed to take advantage of the PID models described in the following.

In [25], an exceptional, empiric, and Arrhenius-like PID model was proposed that includes a regeneration (reversing the PID) term for crystalline silicon PVMs with conventional p-type cells. The authors corroborated the regeneration phenomenon experimentally by exposing the PVM to a considerably high negative bias-voltage to the one causing PID (at night, for instance). Consequently, a trade-off between degradation/regeneration, and generated/consumed power was proposed:

\[
\frac{P}{P_0} = 1 - V_p at^2 h^b e^{-c_1 \kappa T} t
\]  

where \( P \) is the actual obtainable power, \( P_0 \) is the initial power and \( V_p \) is the voltage of the \( i \)-th PVM’s frame (for instance, \( V_p \) can be \( V_{p2}, V_{p3}, \ldots, \) or \( V_{pn} \), as shown in Figure 3); \( a, b, c \) are parameters, \( \kappa \) is the Boltzmann constant, \( h \) is the relative humidity, \( T \) is the temperature and \( t \) is the operation time. Note that applying a negative voltage to a PVM’s frame implies additional hardware. Future research can be directed at designing reconfigurable power converters for injecting this hi-reverse-potential at each frame while disconnecting from the string. The high level of reverse voltage must be supplied with significant efficiency; hence such electronic design could be challenging. Moreover, future studies on the economic implications for this additional energy spent are needed. Additionally, the presented model shows a trade-off between the applied voltage and injection time; research must be conducted to solve this trade-off and take advantage of the previous model.

Similarly, in [26], an experimentally validated, statistics accelerated test model was proposed for estimation of the PID that depends on \( h, T, V_p, \) and \( t \):

\[
\frac{P}{P_0} = 1 - \lim_{t \to \infty} \frac{1 + e^{\frac{V_p - V_0}{\Phi}}}{1 - e^{\frac{V_p - V_0}{\Phi}}}
\]  

where \( c = h_0 / h \) and \( d = e^{(T - T_0) / \phi} \) with \( h_0, T_0, V_0, \Phi, \phi, \tau_0, \tau_1, \) and \( \tau_2 \) as parameters. Unfortunately, the authors did not present evidence for the PID’s reversing, and the model includes many parameters that must be experimentally estimated. Another experimentally validated, semi-empiric degradation model that does not consider the regeneration of the PVM but does consider the frame’s potential can be found in [27]. The shunt resistance \( R_{sh} \) (paralleled resistance with the output voltage of the PVM) is considered as the degradation indicator for the PVM. It can be estimated using the following relationship:

\[
\frac{R_{sh}}{R_{s,0}} = \frac{1}{k_1 + k_2 R_D t}
\]  

where:

\[
R_D = k_3 V_p \frac{k_4}{1 + e^{k_5 h + k_6}} e^{-\frac{c_1 \kappa T}{h}}
\]

and \( k_1, \ldots, k_6, R_{s,0} \) are coefficients for the PVM.

It is worth mentioning that some authors modeled the PID by the shunt resistance degradation and regeneration; such resistance depends on temperature during three lighting phases [28]. They used meteorological data and measured shunting and regeneration kinetics to estimate the PID. However, control of outdoor temperature is quite complicated and energy-demanding.
Although many exciting works are aimed at the PVM’s degradation estimation, they do not offer a schema or information for its mitigation by EMS. Examples of these are [21,29–33].

2.2. Reverse Current Degradation

The RCD seems to have been observed first in 1997 for mono-crystalline silicon PVMs. Hence, researchers proposed to conform arrays of cells inside of the PVMs, paralleled with bypass diodes to redirect/bridge large reverse currents [34]. Additionally, in [35], this degradation phenomenon was also confirmed for both Czochralski and multi-crystalline PVMs.

The authors in [36,37] demonstrated microscopic damages (and hot spots) after making flow a minimal reverse current of 10 mA for 10 min through shaded (amorphous silicon) PVMs. Additionally, in [35], a dramatic drop in the shunt resistance (almost a short circuit) for similar test conditions was demonstrated. The authors also showed that the effect is faster under greater temperatures (70 °C) than ambient ones.

In [38], the authors proposed to add an anti-reverse current diode to each PVM to minimize the RCD. Similarly, in [39], a bypass diode’s interconnection on a string of PVMs (to reduce the components’ quantity) was studied.

Unfortunately, low reverse voltages are expected, and diodes need to overcome the forward bias voltage to bypass the reverse current through a cell, PVM, or a string. While this polarization is achieved, a reverse current can still flow through the panel. Additionally, a small reverse bias saturation current, characteristic of inverse polarization of diodes, allows to waste some energy:

\[ I_s = e_c a_c c_c^2 \left( \frac{1}{n_d} \sqrt{\frac{d_p}{\tau_p}} + \frac{1}{n_a} \sqrt{\frac{d_n}{\tau_n}} \right) \]  

where \( e_c \) is the elementary charge, \( a_c \) is the cross-sectional area, \( c_c \) is the intrinsic carrier concentration in the semiconductor material, \( n_d, n_a \) are the donor and acceptor concentrations at the n side and p side, respectively, \( d_p, d_n \) are the diffusion coefficients of holes and electrons, respectively, and \( \tau_p, \tau_n \) are the carrier lifetimes of holes and electrons, respectively.

Future research could be conducted to design new mathematical models to predict the RCD in the presence of bypass diodes. As mentioned earlier, diodes still allow low reverse currents that can degrade a PVM. Alternatively, cheap circuits to entirely redirect and leverage such reversal currents could be designed in future research.

2.3. Summary

Table 2 summarizes relevant information concerning the models found in the literature for PVMs’ degradation. PRM stands for the number of parameters to estimate. For these studies, no error/precision results were provided, despite being data-based. Future research should provide solid experimental validations and also methodologies for the (online) parameters’ estimations. Since all references listed are aimed at the PID, one can highlight the research presented in reference [25] because it includes a regeneration model. Future research for EMS design should consider diminishing the degradation and even revert it; to achieve the above, economic implications and design of new reconfigurable converters must also be studied.

| Reference | Degradation | Regeneration | PRM | Variables | Complexity |
|-----------|-------------|--------------|-----|-----------|------------|
| [25]      | Yes         | Yes          | 4   | \( V_p, h, T, t, P \) | Low        |
| [26]      | Yes         | No           | 9   | \( V_p, h, T, t, P \) | Medium     |
| [27]      | Yes         | No           | 7   | \( V_p, h, T, t, P \) | Medium     |
| [28]      | Yes         | Yes          | 9   | \( T, t, R_{sh} \) | Medium     |
It is worth mentioning that there are still degradation mechanisms that should be investigated. For instance, engineers have observed undesirable PVM degrading effects with high ripple levels on its output voltage/current. Regularly, the impedance of the PVM is adapted to a load by a power electronic converter, and its high-frequency switching regularly causes such ripples. In this sense, one can infer that rapid current variations, low power factors, and high ripple levels, among other electric stressors, damage the PVM. However, only future research can prove such hypotheses. New chemical compositions for the PVM’s components, for instance, organics, must be investigated for the PID and other degradation and regeneration mechanisms.

Future studies about the design of new EMS considering these degradation mechanisms could result in considerable economic benefits.

3. Battery Degradation

Degradation by electrical stressors in batteries depends primarily on their chemistry. Lead-acid, lithium-ion (Li-ion), nickel metal hydride (NiMH), and lithium iron phosphate (LiFePO$_4$) are the most common compositions.

Since batteries are almost a century more mature technologies than PVMs, many degradation models have been developed. Here only those that could be used to design real-time EMS from the authors’ perspective are analyzed.

Two primary types of battery degradation are regularly considered, namely capacity fade and power fade (CFD and PFD, respectively). Capacity fade is a decrease in the amount of energy that a battery can store. Usually, less than 80% of the initial battery capacity is considered its end of life [40]. Power fade decreases the maximum power that a battery can provide due to an increase in its internal series resistance [41]. It is well known that temperature stress increases the rate of both types of degradation. However, the sole degradation by non-electrical stressors for batteries is not the aim of this paper.

High charge/discharge current levels, cycling, charge and discharge rates (C-Rate and D-Rate, respectively), overcharge, and depth of discharge (DOD), including over-discharge, are well known to degrade anode, cathode, and the active materials of many battery types [15,42]. For instance, Li-ion batteries consist of two electrodes, a porous separator, an electrolyte, and two current collectors, as shown in Figure 4. A binder (not shown) holds the electrode together and maintains electrical conductivity between the active material particles [43]. Each electrode consists of active material particles within which lithium can be stored. Such active materials are known to be degraded by the mentioned stressors, as described in the following. Table 3 describes the nomenclature for this section.

3.1. Capacity-Fade-Type Degradation

Although a discussion of the advantages and disadvantages of batteries’ chemistry is not the purpose of this paper, lead-acid batteries still could be considered within the scope of smart grids. These types of batteries are made from abundant, low-cost materials and nonflammable water-based electrolytes; manufacturing practices that operate with 99% recycling rates substantially minimize the environmental impact of using lead-acid batteries.

A cycling percentage capacity-deficit, and physic-empiric model for lead-acid batteries, was presented in [45,46]:

$$C_{deg} = C_{deg,lim} e^{-5 \left( \frac{ZW}{Z_{IEC}} \right)}$$

where $C_{deg,lim}$ is the capacity at the end of battery life, $Z_W$ is the weighted (function of “normal” operating conditions) number of cycles, and $Z_{IEC}$ is the number of operating cycles that can be obtained under standard conditions (defined in data sheet). Future research can take advantage of this model by optimizing $Z_{IEC}$ within the EMS or improving the battery’s operating conditions.
Figure 4. Illustration of a Li-ion battery cell’s construction. Two electrodes, a porous separator, an electrolyte, and two current collectors are the main components. The released electricity is generated by the difference in the cohesive or bond energies of the metals, oxides, or molecules undergoing the electrochemical reaction because of the electrolyte. The electrolyte contains metal cations reduced (electrons are added) at the cathode, while metal atoms are oxidized (electrons are removed) at the anode [44].

Table 3. Nomenclature for batteries.

| Symbol   | Description                              | Units   |
|----------|------------------------------------------|---------|
| $A_h$    | Ampere-hour throughput                   | Ah      |
| $C_{deg}$| Cycling percentage capacity-deficit      | %       |
| $C_{SOC,I_d}$ | Capacity degradation                     | %       |
| $\delta$ | Cycle-average depth of discharge         | %       |
| $\Delta SOC$ | Cycle state of charge variation         | %       |
| $DOD$    | Depth of discharge                       | %       |
| $I_d$    | Discharge rate                           | Ah      |
| $I_{pulse}$ | Current pulse                           | A       |
| $I_{cal}$ | Capacity fade degradation               | %       |
| $n$      | Actual charge/discharge cycle           |         |
| $N_d$    | Cycles before 20% degradation           |         |
| $OCV$    | Open circuit voltage                     | V       |
| $Q$      | Battery capacity                         | Ah      |
| $Q_{loss}$ | Capacity loss                            | %       |
| $R_s$    | Internal series-resistance               | $\Omega$ |
| $\sigma$ | Cycle-average state of charge           | %       |
| $SOC$    | State of charge                          | %       |
| $t_{CD}/t_{CS}$ | Time for charge-depleting/charge-sustaining | s       |
| $T_c$    | Absolute cell temperature               | $^\circ$C |
| $V$      | Actual voltage                           | V       |
| $Z_{IEC}$ | Data-sheet rated cycles                 |         |
| $Z_{W}$  | Weighted number of cycles               |         |

In [47], the authors empirically characterized a LiFePO$_4$ CFD loss $Q_{loss}$ (percentage) for a 2.2 Ah, 26,650 cylindrical cell battery from A123 Systems. Conditions included five different temperatures (−30, 0, 15, 25, 45, 60 °C), five levels of $DOD$ (90%, 80%, 50%, 20%, and 10%), and four discharges rates ($C/2$, $2C$, $6C$, and $10C$, where $C = 2$ A):

$$Q_{loss} = b e^{-\frac{q_1}{m} A_h}$$

(7)
where \( q_1, q_2, q_3 \) are fitting parameters, \( b_i \) is a D-Rate \((I_d)\) dependent factor, \( R \) is the gas constant, \( T \) is the absolute temperature, and \( A_h \) is the Ampere-hour throughput. New EMS developed in future research could optimize \( A_h \) and \( I_d \) to extend batteries’ lifetime.

Three years later, some of the same authors proposed an improved model in which the temperature plays a fundamental role [48]:

\[
Q_{\text{loss}} = \beta_1 (\beta_2 T^2 + \beta_3 T + \beta_4) e^{(\beta_5 T + \beta_6) I_d A_h^{\beta_7}} + \beta_8 t^{\frac{1}{2}} e^{\frac{e}{RT}}
\]  

(8)

where \( e_a \) is the activation energy, and \( \beta_1, \ldots, \beta_8 \) are parameters.

Furthermore, a semi-empirical model for the same LiFePo4 battery with similar dynamic operating conditions was experimentally validated in [49]. The DOD was included as an input:

\[
Q_{\text{loss}} = \begin{cases} 
(\gamma_1 DOD^2 + \gamma_2 DOD + \gamma_3)k A_h^{\gamma_4} & \text{for C.1} \\
(\alpha_1 e^{\gamma_5 DOD} + \alpha_2 e^{\gamma_6 DOD})k A_h^{\gamma_7} & \text{for C.2} 
\end{cases}
\]

(9)

where C.1 was fitted for \( 10\% \leq \text{DOD} \leq 50\% \) and C.2 for \( \text{DOD} < 10\% \) and \( \text{DOD} > 50\% \). \( k \) is a DOD-dependent parameter \((k = 1 \text{ for constant } \text{DOD})\), and \( \gamma_1, \ldots, \gamma_4, \alpha_1, \alpha_2 \) are parameters. The aging tests were performed in a temperature-controlled environment at 25 °C. Different C-rates and DOD values were combined at a time as the longevity prognosis conditions. According to this model, the DOD has a crucial role in battery degradation; future research on novel EMS can be conducted to include avoiding any deep discharge.

Additionally, in [50], an empirical CFD model (percentage) was experimentally verified for LiFePO4 batteries:

\[
C_{\text{SOC},L_d} = \left( a_c + b_c \Delta_{\text{SOC}} + c_c e^{d_c} \right) n^{1.36}
\]

(10)

where \( a_c, b_c, c_c \) are parameters and \( \Delta_{\text{SOC}} \) is the state of charge (SOC) variation in the \( n \)-th cycle.

The authors in [51] modeled semi-empirically in discrete-time the percentage CFD in an NMC/graphite Li-ion battery \((L_{\text{cal}})\) as a function of temperature and voltage \((V)\):

\[
L_{\text{cal}}(t, T, V) = L_{\text{cal},0} + \sum_{i=1}^{N} \frac{d}{dt_i} (L_{\text{cal}}(t_{i-1}, T_i, V_i)) \Delta t_i
\]

(11)

where:

\[
L_{\text{cal}}(t, T, V) = L_{\text{cal}}(t_0, T, V)(1 + B(T, V)c_{\text{cal}t_i}),
\]

(12)

\[
B(T, V) = c_{\text{AT}} \left( c_V \left( \frac{V - V_0}{\Delta V} \right) + 1 \right),
\]

(13)

\( N \) is the total number of samples, \( c_a, c_V, c_T, c_t, \Delta T \) are parameters, \( \Delta V \) is the average cycle-variation voltage, and \( T_0, V_0, L_{\text{cal},0} \) are initial conditions of temperature, voltage, and CFD, respectively.

It is worth mentioning related results on the batteries’ lifetime, as presented in [52]. Although an analytical model was not proposed, the authors showed up to a 40% increase in Li-ion batteries’ lifetime by two strategies. The former consists of optimizing the recharge level instead of performing a full charge; that is, high battery states of charge decrease battery lifetime. The latter lies on charge electric vehicles as closely as possible to their departure time (diminish the discharge wait times). Note that the authors in this last work performed data analysis instead of using a model to demonstrate the above mentioned findings. Future research could include the previous models to generalize this prior proposal or generate a model for the degradation as a function of the discharge wait times.

The research in [53] showed benefits for Li-ion batteries by reducing the charge and discharge cycles. The above was accomplished by the prediction of the power demand
employing a recurrent neural network. Additionally, the authors in [54] proposed a correlation between a sustained DOD and Li-ion batteries’ lifetime (years):

$$L(DOD) = \left(\frac{DOD}{\ell_1}\right)^{-\ell_2}$$  \hspace{1cm} (14)

where $\ell_1, \ell_2$ are fitting parameters. This simplified empirical model was experimentally validated. Then, the cost of electric vehicle (EV) charging is minimized by optimization, given variable electricity costs.

Additionally, in [55], the authors proposed estimating the number of times a Lithium iron phosphate battery can be fast-charged and fully discharged at a unitary C-rate before its original capacity has decreased by 20%:

$$N_d(I_{ch}) = \eta_1 e^{-\eta_2 I_{ch}} + \eta_3 e^{\eta_4 I_{ch}}$$  \hspace{1cm} (15)

where $\eta_1, \ldots, \eta_4$ are fit parameters. Such parameters were experimentally fitted achieving an effective empiric model. Similarly, the authors proposed and characterized a lifetime–DOD relationship. Future research can be directed to design predictive EMS that optimize the charge rate to avoid premature degradation of the batteries.

The authors in [56] proposed combining SOC, DOD, and $t$ stressors in a physic-empiric degradation model validated with previously obtained data. According to the authors, the SOC contribution (percentage factor) $S_\sigma$ to the degradation is estimated as:

$$S_\sigma = e^{k_\sigma (\sigma - \sigma_{ref})}$$  \hspace{1cm} (16)

where $k_\sigma$ is the SOC stress coefficient, $\sigma_{ref}$ is the reference SOC level usually selected around 0.4 to 0.5, and $\sigma$ is the cycle-average state of charge. The proposed DOD stress model (percentage) is estimated by:

$$S_\delta = \left(k_{\delta 1} \delta k_{\delta 2} + k_{\delta 3}\right)^{-1}$$  \hspace{1cm} (17)

where $k_{\delta 1}, \ldots, k_{\delta 3}$ are empirical coefficients and $\delta$ is the cycle-average depth of discharge. It is worth mentioning that the authors also proposed simplified, empirical models for calendar and cycle aging.

These last proposals can be used for future research to determine an optimal average SOC by EMS design combined with other control objectives.

3.2. Power-Fade-Type Degradation

Theoretical (physics-based) models for PFD (and CFD) can be found in the works [57–59]. However, these models are complex for a real-time application. Their accuracy depends on the availability, the precision of battery parameters [60], and variability, complicating their usage in novel EMS.

On the other hand, empirical models allow estimating the power fade efficiently. Such models provide good results for some operating points, and they are tractable from an EMS-design point of view.

For instance, in [61], another experimentally validated, Arrhenius-like (semi-empirical) formulation was proposed. This model can predict the internal-series-resistance-growth in Li-ion batteries containing blended spinel and layered-oxide positive electrodes:

$$R_{inc} = a_R e^{\frac{t_{ag}}{\Delta t_{av}}} A_R,$$  \hspace{1cm} (18)
Energies 2021, 14, 2117

\[ a_R = \alpha_R + \beta_R (SOC_{\text{min}} - SOC_0) + \gamma_R e^{C_{\text{req}} - C_{\text{req}}} + e(SOC_{\text{min}} - SOC_0), \]

\[ C_{\text{req}} = \begin{cases} 
0 & \text{Ratio} = 0 \\
CR & \text{Ratio} > 0 
\end{cases}, \]

\[ \text{Ratio} = \frac{t_{\text{CD}}}{t_{\text{CD}} + t_{\text{CS}}}. \]

c_{\text{ag}} is the activation energy obtained for the resistance growth process, \( T_c \) is the absolute cell temperature, \( R_u, \alpha_R, \beta_R, \gamma_R, c_R, SOC_0, C_{\text{req}}, SOC_{\text{min}}, C_{\text{req}}, \) are coefficients, \( SOC_{\text{min}} \) is a predefined minimum SOC, and \( t_{\text{CD}}, t_{\text{CS}} \) are the time spent in charge-depleting and charge-sustaining, respectively.

Unfortunately, few power-fade empirical models can be found. Future research on degradation models is a promising opportunity for predicting the power fade’s dynamic behavior. All of the correlated stressor variables can be considered, providing realistic prognoses. Moreover, EMS can integrate developed degradation models and combine other models.

### 3.3. State of Health

Many researchers integrated diverse degradation phenomena in a single indicator, known as the state of health (SOH). However, SOH does not correspond to a particular physical quality. There is no consensus in the industry on how SOH could be determined [62]. Indeed, some researchers consider a capacity fade, others a power fade, and others include both and other phenomena in the same concept as shown in the following.

The equivalent circuit model is the empiric-modeling technique most used to estimate the SOH. This technique provides straightforward and tractable models. From the universe of equivalent-circuit models, it is worth mentioning the semi-empirical model that was experimentally validated in [63]. The authors claimed that the open-circuit voltage (OCV) on Li-ion batteries can be used for SOC estimation and SOH monitoring and proposed the following equality:

\[ OCV = \chi_0 + \chi_1 \frac{1}{1 + e^{\delta_1 (SOC - \delta_2)}} + \chi_2 \frac{1}{1 + e^{\delta_3 (SOC - \delta_4)}} + \chi_3 \frac{1}{1 + e^{\delta_5 (SOC - 1)}} + \chi_4 \frac{1}{1 + e^{\delta_6 SOC}} + \chi_5 SOC \]

(19)

where \( \chi_0, \ldots, \chi_5 \) are linear parameters and \( \delta_1, \ldots, \delta_6 \) are nonlinear parameters. The authors proposed an extended Kalman filter approach to estimate such parameters.

Additionally, the authors in [64,65] proposed to calculate the voltage drop of the battery for a given current, and then calculate the battery’s internal resistance, as follows:

\[ R_s = \frac{OCV - V}{I_{\text{pulse}}} \]

(20)

where \( V \) is the battery voltage and \( I_{\text{pulse}} \) is the Ampere value of a short current pulse. This physic-empiric degradation model allowed the authors to show that a worn battery has considerable internal resistance and releases more heat during the charge and discharge. Hence, the safety of the occupants of an electric vehicle can be compromised.

On the other hand, researchers in [66] demonstrated that the derivative of battery capacity \( Q \) with respect to \( V \) reflects identifiable \( dQ/dV \) peaks related to its energy-absorption ability (during constant-rate charging). The analysis of such behavior was named incremental capacity analysis (ICA) and is widely used to estimate SOH. A remarkable study on the real-time estimation of \( dQ/dV \) for Li-ion battery packs can be found in [67]. The following experimentally validated model was proposed:

\[ \frac{dQ}{dV} = \frac{dQ}{d(OCV + R_s I_{\text{ch}})} \approx \frac{dQ}{dOCV} \]

(21)
where \( R_s \) is the internal series resistance.

Future research aimed at minimizing the degradation of batteries should consider at least the models mentioned above. Novel EMS could combine and take advantage of these degradation models while providing an efficient and uninterrupted energy supply.

### 3.4. Summary

Table 4 summarizes relevant information concerning empiric degradation models for batteries. Future research on EMS’ design can take considerable economic advantage of these models from an electrical control perspective.

**Table 4.** Degradation models with electrical-related input for Li-ion batteries. CFD: capacity fade; PFD: power fade; SOH: state of health.

| Reference | Type | PRM | Variables | Error | Complexity |
|-----------|------|-----|-----------|-------|------------|
| [45,46]  | CFD  | 3   | \( Z_W, C_{deg} \) | -     | Low        |
| [47]     | CFD  | 4   | \( DOD, I_d, T, A_{hr}, Q_{loss} \) | -     | Medium     |
| [48]     | CFD  | 8   | \( I_d, T, A_{hr}, Q_{loss} \) | 5%    | High       |
| [49]     | CFD  | 6   | \( DOD, I_d, A_{hr}, Q_{loss} \) | 1.75 RMS | Low        |
| [50]     | CFD  | 3   | \( DOD, I_d, n, C_{SOC, Id} \) | \( 1.5 \times 10^{-5} \) RMS | Low        |
| [51]     | CFD  | 6   | \( T, V, I_{cal} \) | -     | Medium     |
| [54]     | CFD  | 2   | \( DOD, L \) | -     | Low        |
| [55]     | CFD  | 4   | \( I_d, N_d \) | 5.4%  | Low        |
| [56]     | CFD  | 2   | \( \sigma, S_{r} \) | 14%   | Low        |
| [56]     | CFD  | 3   | \( \delta, S_{g} \) | 14%   | Low        |
| [61]     | PFD  | 7   | \( SOC, T, A_{hr}, R_{inc} \) | \( 2.1 \times 10^{-5} \) RMS | Low        |
| [63]     | SOH  | 11  | \( SOC, OCV \) | 1.01% | High       |
| [67]     | SOH  | 11  | \( OCV, R_s, I, dQ/dV \) | -     | High       |

Note: - means not provided.

It is worth mentioning that there are still battery degradation mechanisms that must be investigated. For instance, the degrading effects of high ripple levels and oscillations in the demand regime must be verified. The high ripple levels are caused by the switching of the power electronic converters connected as loads. Fluctuations can be produced inherently by the energy consumer. In this sense, one can infer that rapid current variations and low power factors, among others, damage a battery. However, only future research can examine such hypotheses. Additionally, new chemical compositions for the batteries must be investigated for electrical-nature degradation mechanisms.

Additionally, some authors have documented a regeneration phenomenon during the rest between charge/discharge (also called the self-recharge phenomenon)—a Li-ion battery shows a sudden (and temporary) incremental increase in the capacity available for the next cycle [68–70]. The above can almost seem opposite to the results in [52], where it was claimed that the degradation decreases if the rest time is null (avoiding 100% recharges). Since both claims were obtained empirically, frontier research could be conducted to solve the dilemma.

Moreover, regeneration models could not be found in the literature despite the fact that EMS can take considerable advantage of them. The closest proposal can be found in [71], where the authors presented a remarkable study on lead batteries degradation-detection and remediation of sulfation (regeneration) by a recharge profile/control and pressure-sensing. Hence, promising future research is foreseen on this topic.

Battery degradation still needs further research and must include new chemistries, such as Ni-rich cathodes, Li-rich cathodes, or lithium–sulfur. Deep neural networks could
be a tool for developing more complete degradation models of batteries to include them in novel EMS.

4. Fuel Cell Degradation

Many types of fuel cells have been developed to date, and extensive research has been done to identify the mechanisms that degrade the fuel cell components [72]. However, empirical degradation-estimation models by electrical stressors are not easily found. There are also few pure analytic models with electrical stressors; however, they are complicated with many parameters and electrochemical variables that must be estimated or measured. Pure analytic models with electrical stressors for fuel cells are not the subject of this paper.

The main components of a proton exchange membrane fuel cell (PEMFC) are illustrated in Figure 5.

Figure 5. Illustration of a proton exchange membrane fuel cell (PEMFC) construction. Two electrodes, catalyst and gas diffusion layers, and an electrolyte membrane are their main components. Some hydrogen atoms are separated, producing an electron flux (electric current), and then joined with oxygen atoms to form water and vapor.

Regularly, a fuel cell system should be capable of a minimum lifetime of 40,000 h (with 8000 h of uninterrupted service and a minimum consumption of 80% of the rated power). For automotive applications, 5000 h at a degradation rate of less than 1% each 1000 h at least are required for 20,000 operational hours [72]. The more known electrical stress degradation phenomena result in power losses by catalyst degradation. Literature directly relates the internal resistance and voltage drop with degradation. Temperature and humidity are factors that increase the degradation rates by electrical stress.

Table 5 describes the terminology for this section.

4.1. Catalyst Surface Degradation

A catalyst degrades over time, which means that it loses catalytic activity due to various aging processes. However, some premature degradation effects have been observed with excessive current load profiles (higher than the manufacturer’s recommendations).

In [73], a simplified (physic-empiric) model for the polarization’s curve degradation in a small PEMFC was proposed and experimentally validated. According to the authors, the catalyst surface degradation results in a decrease in the PEMFC’s voltage. This change in voltage $\Delta V$ can be estimated as:

$$\Delta V = v \frac{S}{S_0}$$

(22)

where $v$ is a slope constant determined empirically, $S$ is the catalyst’s electrochemically active surface area, and $S_0$ is the initial value for such an area. The degraded polarization
curve can be approximated by a composition of the polarization curve of the PEMFC before any degradation $V_{f0}(i_f)$:

$$V_{fc} = \varphi \ln \left( V_{f0}(i_f) \right) + V_{ocv}$$  

(23)

where $i_f$ is the current density, $V_{ocv}$ is the open-circuit voltage before any degradation,

$$\varphi = \frac{V_{pmax} + \Delta V - V_{ref}}{\ln(V_{pmax})},$$

$V_{pmax}$ is the voltage at the maximum power output voltage, and $V_{ref}$ is a constant.

Future research could be conducted to determine the electrical stressors that influence the active surface area, including regeneration phenomena. Several hypotheses can be established in such a sense since there are many electrical stressors, such as ripple levels, oscillations' frequency, voltage/current rate, etc.

Table 5. Nomenclature for fuel cells.

| Symbol | Description | Units |
|--------|-------------|-------|
| $A_f$  | Airflow rate | CFM   |
| $b_{cell}$ | Tafel slope | V     |
| $\Delta V$ | Voltage drop | V     |
| $F_u$  | Fuel utilization | %     |
| $i_0$  | Exchange current density | Am$^{-2}$ |
| $i_{af}$ | History index for the airflow rate |       |
| $i_{mne}$ | History index for the methanol concentration |       |
| $i_{fc}$ | Actual current density | Am$^{-2}$ |
| $i_{mf}$ | History index for the methanol flow rate |       |
| $i_t$  | History index for the inner temperature |       |
| $\lambda$ | Voltage oscillation amplitude | V     |
| $r_d$  | Degradation rate | %     |
| $S$    | Catalyst’s EC active surface area | m$^2$ |
| $\tau_{cycle}$ | Remaining life | year |
| $V_{act}$ | Activation overvoltage | V     |
| $V_{fc}$ | Actual output voltage | V     |
| $V_{\Omega,loss}$ | Ohmic overvoltage loss | V     |
| $V_{ocv}$ | Open circuit voltage before any degradation | V     |
| $V_{pmax}$ | Voltage at the maximum power output voltage | V     |
| $V_{TS}$ | Cell voltage | V     |

4.2. Degradation by Voltage Oscillations

This type of degradation has been studied in fuel cell longevity terms. The authors in [74] presented a combined empirical and physic-empiric remaining life model (years) for a small PEMFC. Their model considers the effect of the actual voltage level, temperature, and humidity, as well as the amplitude of voltage oscillations:

$$\tau_{cycle} = a_v e^{-k_v V_{TS} a_T e^{-k_T T}(a_h ln(h) + k_h)}(1 - a_\lambda \lambda)$$  

(24)

where $a_v, a_T, a_h, a_\lambda, k_h, k_v, k_T$ are constants and $\lambda$ is the voltage oscillation amplitude. This model was experimentally validated to supply power to sensor networks.

Future research on EMS design must consider that high oscillations on the voltage and low averaged voltages prematurely degrade the fuel cell.

4.3. Ohmic Overvoltage Degradation

This type of degradation can be understood as a slow transport of reactants from the fuel cell electrolyte to the electrode surface. In [75], a semi-empiric, experimentally validated degradation model for a low-pressure PEMFC was presented. This model was
characterized by bus city driving cycles in that research. The ohmic overvoltage loss (the ohmic overvoltage is $V_{\Omega} = R_{fc}i_{fc}$ where $R_{fc}$ is the equivalent parallel resistance of the fuel cell) can be estimated by:

$$V_{\Omega,\text{loss}} = (v_1 T^2 - v_2 T + v_3 + v_4 t_{fc})i_{fc}$$  \hspace{1cm} (25)$$

where $v_1, \ldots, v_4$ are parameters and $t_{fc}$ is the stack operating time according to the driving cycle. $T$ is used for the absolute device’s temperature.

Alternatively, for a single direct methanol fuel cell (DMFC), the area-specific resistance-degradation can be estimated by [76]:

$$R_e = \mu_1 T + \mu_2 i_t + \mu_3 i_{mf} + \mu_4 i_{af}$$  \hspace{1cm} (26)$$

where $\mu_1, \ldots, \mu_5$ are parameters, $i_t$ is the history index for the inner temperature of the cell, $i_{mf}$ is the history index for the methanol flow rate, and $i_{af}$ is the history index for the airflow rate.

The Tafel slope $b_{cell}$ (effect of loss in the voltage of the cell obtained by $V_{TS} = b_{cell} \ln(i_{fc})$) can be estimated by:

$$b_{cell} = \mu_6 + \mu_7 A_f + \mu_8 T + \mu_9 i_{cme} + \mu_{10} i_{af}$$  \hspace{1cm} (27)$$

where $\mu_6, \ldots, \mu_9$ are parameters, $A_f$ is the airflow rate and $i_{cme}$ is the history index for the methanol concentration. This model can be considered semi-empirical since degradation was observed and modeled over time by linear regressions.

Future research could consider the fuel cell overcurrent as a mechanism for ohmic overvoltage loss degradation in novel EMS. Electrical stressors could also complement the last two models; these are hypotheses that must be demonstrated by future research.

### 4.4. Activation Overvoltage Degradation

Activation overvoltage can be considered the energy lost due to the slowness of electrochemical reactions at the anode and the fuel cell’s cathode electrodes. In [75], a semi-empiric, experimentally validated model for the activation overvoltage $V_{act}$ was proposed:

$$V_{act} = v_1 T + (v_2 T + v_3 + v_4 t)T \sigma_f$$  \hspace{1cm} (28)$$

where:

$$\sigma_f = \ln\left(i_{fc} + (v_5 T^2 - v_6 T + v_7 + v_8 t)\right)$$

and $v_1, \ldots, v_8$ are parameters.

In [77–79], it was proposed that for a solid oxide fuel cell (SOFC):

$$V_{act} = \frac{RT}{2a_z F_c} \sinh^{-1}\left(\frac{i_{fc}}{2i_0}\right)$$  \hspace{1cm} (29)$$

where $i_0$ is the current exchange density, $F_c$ is Faraday’s constant, and $a_z$ is a transfer coefficient. This model was obtained by a physico-empiric approach and validated numerically.

Future research could consider the fuel cell overcurrent as a mechanism for activation overvoltage degradation in novel EMS. Electrical stressors could also complement the last models; these are hypotheses that must be demonstrated by future research.

### 4.5. Degradation Rate

The authors in [80] analyzed data collections of experimental results from international and local research groups. That resulted in a percentage so-called degradation rate ($r_d$) model for SOFCs:

$$r_d = \frac{r_1 F_u + r_2}{1 + e^{r_3 i_{fc}/2}} \left( e^{r_4 i_{fc}} - 1 \right)$$  \hspace{1cm} (30)$$
where $F_u$ is the fuel utilization and $r_1, \ldots, r_5$ are parameters. The parameters for this empiric model were fitted from such data collections. Note that this model includes the current density as an exponential factor of the degradation increment. Novel EMS designed in future research could consider this model to increase the longevity of SOFCs. Additionally, in future research, other electrical stressors could be studied for the degradation rate.

4.6. Summary

Table 6 summarizes relevant models’ information for EMS design. Fuel cells are complicated devices that require extreme care in the power-extraction regime recommended by the manufacturer. However, as reviewed in this chapter, some phenomena must be considered additionally. The inclusion of additional electric stressors can extend almost all of the models presented in this section. For instance, high current variations could damage the fuel cell, and degradation models cannot be found in the literature. How high can be the current variations or their frequency to avoid premature degradation of the fuel cell? Despite the above, future research could be conducted to combine several degradation models in EMS. There is a broad research gap for these devices, including those of novel chemistries.

Table 6. Degradation models with electrical-related input for fuel cells. DMFC: direct methanol fuel cell; SOFC: solid oxide fuel cell.

| Reference | Fuel Cell | PRM | Variables | Error | Complexity |
|-----------|-----------|-----|-----------|-------|------------|
| [73] PEMFC 4 | $i_{fc}, \Delta V, V_{fc}$ | 4% | High |
| [74] PEMFC 7 | $V_{fc}, T, \lambda, \tau_{cycle}$ | - | Medium |
| [75] PEMFC 4 | $T, i_{fc}, t_{fc}, V_{loss}$ | - | Medium |
| [76] DMFC 5 | $T, i_{fc}, t_{fc}, V_{cell}$ | 0.9 $R^2$ | High |
| [77–79] SOFC 1 | $T, i_{fc}, i_{0}, n_{fc}, V_{act}$ | - | High |
| [80] SOFC 5 | $F, T, i_{fc}, r_d$ | - | High |

Note: - means not provided.

5. Supercapacitor/Ultracapacitor Degradation

A supercapacitor has 10 to 1000 magnitudes more power density than a regular capacitor. SCs are regularly used in smart grids of any scale to absorb fast current/voltage variations that could damage other connected devices. SCs operate through electrochemistry phenomena and can be classified into three types: double-layer (Ionic) SCs, pseudocapacitors, and hybrids [81].

The double-layer capacitor uses a physical mechanism that generates an electric double-layer (the state where a very thin ionosphere is formed between electrolyte and electrode boundary). The collector is impregnated with an electrolyte. The electric double-layer is formed on the active material surface (activated carbon, mesoporous carbon, carbon nanotubes, and graphene are often used) in contact with the liquid electrolyte. A separator with high insulating properties against ion penetration is positioned between both electrodes to prevent short-circuiting (see Figure 6).

A pseudocapacitor is built with electrodes of different materials. A faradaic charge transfer (similar to that occurring in batteries) is originated by a high-speed sequence of reversible redox, electroosorption or intercalation processes on the surface of these electrodes. Materials undergoing these types of processes include conducting polymers and several metal oxides, such as $\text{RuO}_2$, $\text{MnO}_2$, and $\text{Co}_3\text{O}_4$ [82].
Research on SC technology shows that overvoltage, deep-cycling, high temperature, and high charge/discharge current are the leading electrical stressors. Effects of degradation include capacitance fading, equivalent series resistance (ESR) increase, and leakage current [83,84]. Unfortunately, very few electrical stress models can be found in the literature.

Table 7 describes the nomenclature for this section.

![Basic schematic for a super-capacitor (SC). The device has an active material (e.g., carbon, MnO₂, LiCoO₂), current collectors, a separating membrane and electrolyte, (e.g., Na₂SO₄, or LiPF₆ solutions).](image)

Table 7. Nomenclature for supercapacitors.

| Symbol | Description                           | Units |
|--------|---------------------------------------|-------|
| \( L_a \) | Expected operating life               | h     |
| \( L_r \) | Rated life                            | h     |
| \( T_a \) | Core temperature                      | °C    |
| \( T_r \) | Temperature for the rated life        | °C    |
| \( V_a \) | Actual operational voltage            | V     |
| \( V_r \) | Rated voltage                         | V     |

5.1. Overvoltage Degradation

In [85], the authors developed a semi-empirical model for the expected operating life (time-to-failure in hours) \( L_a \). The time-to-failure was established as a function of the temperature and the operating voltage for an LS Mtron SC:

\[
L_a = L_r e^{(E_s(T_r - T_a) + j(V_a - V_r)}
\]  

(31)

where \( L_r \) is the rated life, \( T_r \) is the rated temperature corresponding to the rated life, \( T_a \) is the core temperature of the SC, \( V_a \) is the actual operational voltage, \( V_r \) is the rated voltage, and \( E_s, j \) are parameters. This model was experimentally validated.

Future research can be conducted to model the degradation effect by DOD, current/voltage rate, oscillations frequency, and amplitude. Additionally, novel EMS must consider the degradation stressors in future research.

5.2. Summary

In Table 8, the relevant information for the model of Equation (31) is summarized. The development of empiric models for SC is incipient. Degradation phenomena by a broad spectrum of stressors such as voltage/current ripple and frequency are still unsolved or unmodeled. At most, in [86], it was shown that the current waveform influences the degradation of DC-link aluminum electrolytic capacitors. There is a wide gap for future research about the degradation of SC.
Table 8. Degradation model with electrical-related input for super-capacitors.

| Reference | Brand | PRM | Variables | Error | Complexity |
|-----------|-------|-----|-----------|-------|------------|
| [85]      | LS Mtron | 2   | $T_a$, $V_a$, $L_a$ | 7.97 h | Low        |

6. Degradation in Eolic, Tidal, and Other Generators and Energy Conversion Systems

Many other green-energy generator devices are involved in smart grids. Mostly, electromechanical generators, such as eolic and tidal, are used due to their enormous capacity. Known degradation stressors for these generators include mechanical wear and windings deterioration due to harsh environmental conditions. Although they are out of the scope of this paper, electrical-stressors’ degradation should be studied for electromechanical devices in future research. For instance, rapid fluctuations, high amplitude oscillations, frequency, and other power-quality concerns should be studied for degradation phenomena. For instance, high frequency (>1 kHz) pulse width modulation (PWM) transients can stress the polymer windings insulation in electromechanical generators [87].

On the other hand, electronics are a fundamental component in smart grids. Electronics’ reliability relies on their design, build, and components’ quality [88–91]. Degradation effects caused by electrical stressors in capacitors [86] and power switches [92,93] have been demonstrated. Some researchers aimed to study degradation of power electronic converters by environmental conditions [94], humidity and condensation [95], thermal loading [96], and others [97]. However, no empirical degradation models have been developed, to the authors’ knowledge. Future research to estimate and predict electronics degradation by electrical stressors can be conducted; there is no doubt that these devices are especially susceptible to overvoltage and overcurrent.

Increasing emphasis is being placed on cables, inverters, junction boxes, and interconnects. For instance, in [98,99], the degradation phenomenon that was caused by hours of damp heat and atmospheric corrosion on PVM connectors was studied.

However, the study of the degradation of smart grid components, unlike reliability, must go further and study the degradation mechanisms by developing dynamic models of operation. EMS can take advantage of any degradation model, and future research could be conducted to simultaneously diminish several degradation mechanisms with economic benefits that seem considerable.

Other energy generation/storage devices, such as power harvesters, have recently been gaining importance due to their promised high life cycle. Examples are organic fuel cells, the revisited flywheel configured for electrical storage [100,101], or wind power optimization [102]. So far, no realistic degradation studies were found for these devices.

7. Conclusions and Additional Opportunity Areas

Nowadays, there is a trend to develop EMS that minimize the degradation effects on electrochemical devices. Models of degradation by electrical stressors can significantly improve their operative life and the associated economic costs. Novel EMS could simultaneously take advantage of several of these models to extend the longevity of devices.

With those objectives in mind, treatable degradation models for the most aggressive electrical stressors are needed. For instance, studies about the ripple level from PWM switching on Batteries, PVMs, fuel cells, SC, and interconnected devices are required.

Table 9 summarizes the studies regarding stressors for electrochemical devices that could be found in the literature. Some stressors may not indicate a precise concept, and a specific device’s technology is not particularized. Nevertheless, there is a wide gap in the study of electrical degradation mechanisms for several electrochemical devices, and studies for electrical stress degradation in non-electrochemical devices are, in practical terms, null.

It is worth mentioning that empirical and semi-empirical models are prone to fail to capture parameter inter-dependencies or extract hidden correlations from the data. Future research can be directed at obtaining more accurate models.
Additionally, few regeneration phenomena from an electrical perspective have been documented.

Table 9. Summary of electrical-stressors studies for relevant smart grid devices.

| Device     | DOD  | SOC  | Cycling | Overvoltage | Overcurrent | V/I Rate | Reverse V/I | Amp. (Osc.) | Freq. (Osc.) |
|------------|------|------|---------|-------------|-------------|----------|-------------|-------------|--------------|
| Battery    | [42], [49–52], [54–56]. | [52,56], [61,63,67], [66]. | [42], [45–47], [50,52], [53], [56–59]. | [42,65,67], [66]. | [42,57–59], [59,64]. | [47–52], [55], [57–59], [61,64]. | [68–71]. |             |             |
| Fuel cell  | N/A  | N/A  | [72].   | [72–74].    | [72–74].    | [72,73], [75–80]. | [73]. | [74]. |             |
| PVM        | N/A  | N/A  | N/A     | [29–31].    | [29–31].    | [30]. | [23–28], [34–39]. |             |
| Supercapacitor | [83,84]. | [83,84]. | [83–85]. | [83,84]. |             |             |             |             |
| Converter  | N/A  | N/A  | [89]    |             |             |             |             |             | [90,91]. |
| Power switch | N/A  | N/A  |         |             |             |             |             |             | [92,93]. |
| Capacitor  | N/A  | N/A  |         |             |             |             |             |             | [86].   |
| Wiring     | N/A  | N/A  | N/A     |             |             |             |             |             | [87].   |

Notes: Blank cells means not found. N/A means not applicable.

Author Contributions: Conceptualization, M.A.R.L.; formal analysis, M.A.R.L.; investigation, M.A.R.L., F.J.P.P., and A.G.S.S.; resources, F.J.P.P., and A.G.S.S.; writing—original draft preparation, M.A.R.L., F.J.P.P., and A.G.S.S.; visualization, M.A.R.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: The authors would like to thank CONACYT México for the Cátedras ID 4155 and 6782 and Alma Pamela Rodríguez Huerta for her image design.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. White, D.; James, W. Digital computer simulation for prediction and analysis of electromagnetic interference. *IRE Trans. Commun. Syst.* 1961, 9, 148–159. [CrossRef]
2. Sapolsky, R.M. *Stress, the Aging Brain, and the Mechanisms of Neuron Death*; The MIT Press: Cambridge, MA, USA, 1992.
3. Meeker, W.Q.; Escobar, L.A. A review of recent research and current issues in accelerated testing. *Int. Stat. Rev./Rev. Int. Stat.* 1993, 61, 147–168. [CrossRef]
4. Gorjian, N.; Ma, L.; Mittinty, M.; Yarlagadda, P.; Sun, Y. A review on degradation models in reliability analysis. In *Engineering Asset Lifecycle Management*; Springer-Verlag: London, UK, 2010; pp. 369–384.
5. Konstantinou, C. Towards a Secure and Resilient All-Renewable Energy Grid for Smart Cities. *arXiv* 2021, arXiv:2101.10570.
6. Li, Q.; Wang, T.; Li, S.; Chen, W.; Liu, H.; Breaz, E.; Gao, F. Online extremum seeking-based optimized energy management strategy for hybrid electric tram considering fuel cell degradation. *Appl. Energy* 2021, 285, 116505. [CrossRef]
7. Zhang, Z.; Guan, C.; Liu, Z. Real-time optimization energy management strategy for fuel cell hybrid ships considering power sources degradation. *IEEE Access* 2020, 8, 87046–87059. [CrossRef]
8. Zhu, D. Energy Management of the Embedded Hydride Tanks Considering Efficiency Degradation and Life Span on Fuel Cell Vehicles. Ph.D. Thesis, Bourgogne Franche-Comté, Bourgogne, France, 2020.
9. Aghdam, F.H.; Kalantari, N.T.; Mohammadi-Ivatloo, B. A chance-constrained energy management in multi-microgrid systems considering degradation cost of energy storage elements. *J. Energy Storage* 2020, 29, 101416. [CrossRef]
10. Guo, N.; Zhang, X.; Zou, Y.; Guo, L.; Du, G. Real-time predictive energy management of plug-in hybrid electric vehicles for coordination of fuel economy and battery degradation. *Energy* 2020, 214, 119070. [CrossRef]
11. De Pascali, L.; Biral, F.; Onori, S. Aging-aware optimal energy management control for a parallel hybrid vehicle based on electrochemical-degradation dynamics. *IEEE Trans. Veh. Technol.* 2020, 69, 10868–10878. [CrossRef]
12. Li, F.; Cañizares, C.; Lin, Z. Energy management system for dc microgrids considering battery degradation. In *Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM)*, Montreal, QC, Canada, 3–6 August 2020; pp. 1–5.
13. Collath, N.; Englberger, S.; Josien, A.; Hesse, H. Reduction of Battery Energy Storage Degradation in Peak Shaving Operation through Load Forecast Dependent Energy Management. In Proceedings of the NEIS 2020, Conference on Sustainable Energy Supply and Energy Storage Systems, VDE, Hamburg, Germany, 14–15 September 2020; pp. 1–6.

14. Datta, J.; Das, D. Stochastic Energy Management of grid-connected microgrid considering battery degradation cost and renewables penetration. In Proceedings of the 2020 IEEE International Conference on Power Systems Technology (POWERCON), Bangalore, India, 14–16 September 2020, pp. 1–6.

15. Woody, M.; Arbaba-Zadeh, M.; Lewis, G.M.; Keoleian, G.A.; Stefanopoulos, A. Strategies to limit degradation and maximize Li-ion battery service lifetime-Critical review and guidance for stakeholders. J. Energy Storage 2020, 28, 101231. [CrossRef]

16. Prokop, M.; Draškela, M.; Bouzek, K. Review of the experimental study and prediction of Pt-based catalyst degradation during PEM fuel cell operation. Curr. Opin. Electrochem. 2020, 20, 20–27. [CrossRef]

17. Sorrentino, A.; Sundmacher, K.; Vidakovic-Koch, T. Polymer Electrolyte Fuel Cell Degradation Mechanisms and Their Diagnosis by Frequency Response Analysis Methods: A Review. Energies 2020, 13, 5825. [CrossRef]

18. Xu, K.; Zhao, X.; Hu, X.; Guo, Z.; Ye, Q.; Li, L.; Song, J.; Song, P. The review of the degradation mechanism of the catalyst layer of membrane electrode assembly in the proton exchange membrane fuel cell. In IOP Conference Series: Earth and Environmental Science; IOP Publishing: Dalian, China 2020; Volume 558, p. 052041.

19. Lindig, S.; Kaaya, I.; Weiß, K.A.; Moser, D.; Topic, M. Review of statistical and analytical degradation models for photovoltaic modules and systems as well as related improvements. IEEE J. Photovolt. 2018, 8, 1773–1786. [CrossRef]

20. Jamil, W.J.; Rahman, H.A.; Shaari, S.; Salam, Z. Performance degradation of photovoltaic power system: Review on mitigation methods. Renew. Sustain. Energy Rev. 2017, 67, 876–891. [CrossRef]

21. Kaaya, I. Photovoltaic Lifetime Forecast: Models for Long-Term Photovoltaic Degradation Prediction and Forecast. Ph.D. Thesis, University of Malaga, Malaga, Spain, 2020.

22. Kumar, M.; Kumar, A. Performance assessment and degradation analysis of solar photovoltaic technologies: A review. Renew. Sustain. Energy Rev. 2017, 78, 554–587. [CrossRef]

23. Miranda, H.F.B.; da Costa, L.P.; Soares, S.O.; da Silva, J.V. Potential induced degradation (PID): Review. In Proceedings of the 2020 IEEE PES Transmission & Distribution Conference & Exhibition-Latin America (T&D LA), Montevideo, Uruguay, 28 September–October 2020, pp. 1–6.

24. Sun, G.; Tu, X.; Wang, R. Research on the potential-induced degradation (PID) of PV modules running in two typical climate regions. Clean Energy 2019, 3, 222–226. [CrossRef]

25. Annigoni, E.; Virtuani, A.; Sculati-Meillard, F.; Ballif, C. Modeling Potential-Induced Degradation (PID) of Field-Exposed Crystalline Silicon Solar PV Modules: Focus on a Regeneration Term. In Proceedings of the 2017 IEEE 44th Photovoltaic Specialist Conference (PVSC), Washington, DC, USA, 25–30 June 2017; pp. 2794–2798.

26. Hattendorf, J.; Loew, R.; Gnehr, W.; Wulff, L.; Koekten, M.; Koshnicharov, D.; Bluaermei, A.; Esquivel, J. Potential induced degradation in mono-crystalline silicon based modules: An acceleration model. In Proceedings of the 27th European PV Solar Energy Conference, Frankfurt, Germany, 24–28 September 2012; pp. 3405–3410.

27. Braisaz, B.; Duchayne, C.; Van Iseghem, M.; Radouane, K. PV aging model applied to several meteorological conditions. In Proceedings of the 29th European Photovoltaic Solar Energy Conference and Exhibition (EUPVSEC), Amsterdam, The Netherlands, 22–26 September 2014; pp. 22–26.

28. Taubitz, C.; Schütze, M.; Kröber, M.; Koentopp, M.B. Potential induced degradation: Model calculations and correlation between laboratory tests and outdoor occurrence. In Proceedings of the 29th European Photovoltaic Solar Energy Conference and Exhibition, Amsterdam, The Netherlands, 22–26 September 2014; pp. 2490–2494.

29. Hocine, S.; Kaaya, I.; Weiß, K.A.; Moser, D.; Topic, M. Review of statistical and analytical degradation models for photovoltaic modules and systems as well as related improvements. Renew. Energy 2021, 164, 603–617. [CrossRef]

30. Liu, J. Degradation & Partial Shading Study of Photovoltaic Modules in the Field: Enabled by Time-Series Current-Voltage & Power Analysis. Ph.D. Thesis, Case Western Reserve University, Cleveland, OH, USA, 2020.

31. Osipina, B.; Parra, J.S.; Franco, E.; Orozco-Gutierrez, M.L.; Bastidas-Rodríguez, J.D. Quantification of Photovoltaic Modules Degradation in a String Using Model Based Indicators. In Proceedings of the 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EIEEIC/I&CPES Europe), Palermo, Italy, 12–15 June 2018; pp. 1–5.

32. Kichou, S.; Silvestre, S.; Nofuentes, G.; Torres-Ramírez, M.; Chouder, A.; Guasch, D. Characterization of degradation and evaluation of model parameters of amorphous silicon photovoltaic modules under outdoor long term exposure. Energy 2016, 96, 231–241. [CrossRef]

33. Bastidas-Rodríguez, J.D.; Franco, E.; Petrone, G.; Ramos-Paja, C.A.; Spagnuolo, G. Quantification of photovoltaic module degradation using model based indicators. Math. Comput. Simul. 2017, 131, 101–113. [CrossRef]

34. Herrmann, W.; Wiesner, W.; Vaassen, W. Hot spot investigations on PV modules-new concepts for a test standard and consequences for module design with respect to bypass diodes. In Proceedings of the Conference Record of the Twenty Sixth IEEE Photovoltaic Specialists Conference-1997, Anaheim, CA, USA, 29 September–3 October 1997; pp. 1129–1132.

35. Herrmann, W.; Adrian, M.; Wiesner, W.; Rheinland, T. Operational behaviour of commercial solar cells under reverse biased conditions. In Proceedings of the Second World Conference on Photovoltaic Solar Energy Conversion. Citeseer, Vienna, Austria, 6–10 July 1998; pp. 2357–2359.
36. Sidawi, J.; Habchi, R.; Abboud, N.; Jaafari, A.; Al Allouch, F.; Moussa, G.E.H.; Aillerie, M.; Petit, P.; Zegaoui, A.; Salame, C. The effect of reverse current on the dark properties of photovoltaic solar modules. *Energy Procedia* **2011**, *6*, 743–749. [CrossRef]

37. Sidawi, J.; Zarakat, C.; Habchi, R.; Bassil, N.; Salame, C.; Aillerie, M.; Charles, J.P. Evolution of photovoltaic solar modules dark properties after exposition to electrical reverse stress current inducing thermal effect. *Microelectron. Int.* **2014**, *31*, 90–98. [CrossRef]

38. Zhang, X.; Zhu, L.; Zhang, J.; Bao, F.; Wang, W.; Wang, F. Discussion on the necessity of anti-reverse current diode in photovoltaic lightning protective combined box. *Low Volt. Appar.* **2013**, *8*, 36–38.

39. Jung, T.H.; Kang, G.H.; Ahn, H.K. Optimal Design of PV Module with Bypass Diode to Reduce Degradation due to Reverse Excess Current. *Trans. Electr. Electron. Mater.* **2014**, *15*, 279–283. [CrossRef]

40. Spotnitz, R. Simulation of capacity fade in lithium-ion batteries. *J. Power Sources* **2003**, *113*, 72–80. [CrossRef]

41. Zhang, J.; Lee, J. A review on prognostics and health monitoring of Li-ion battery. *J. Power Sources* **2011**, *196*, 6007–6014. [CrossRef]

42. Cherry, J.; Merichko, T. *Battery Durability in Electrically Vehicle Applications: A Review of Degradation Mechanisms and Durability Testing*; Prepared for Environmental Protection Agency: Ann Arbor, MI, USA, 2015.

43. Marquis, S.G.; Sulzer, V.; Timms, R.; Please, C.P.; Chapman, S.J. An asymptotic derivation of a single particle model with electrolyte. *J. Electrochem. Soc.* **2019**, *166*, A3693. [CrossRef]

44. Dingrando, L.; Barr, L. *Chemistry: Matter and Change*; McGraw-Hill Glencoe: New York, NY, USA 2005.

45. Hamedi, A.S.; Rajabi-Ghahnavieh, A. Explicit degradation modelling in optimal lead-acid battery use for photovoltaic systems. *IET Gener. Transm. Distrib.* **2016**, *10*, 1098–1106. [CrossRef]

46. Schiffer, J.; Sauer, D.U.; Bindner, H.; Cronin, T.; Lundsager, P.; Kaiser, R. Model prediction for ranking lead-acid batteries according to expected lifetime in renewable energy systems and autonomous power-supply systems. *J. Power Sources* **2007**, *168*, 66–78. [CrossRef]

47. Wang, J.; Liu, P.; Hicks-Garner, J.; Sherman, E.; Soukiazian, S.; Verbrugge, M.; Tatari, H.; Musser, J.; Finamore, P. Cycle-life model for graphite-LiFePO4 cells. *J. Power Sources* **2011**, *196*, 3942–3948. [CrossRef]

48. Marquis, S.G.; Sulzer, V.; Timms, R.; Please, C.P.; Chapman, S.J. An asymptotic derivation of a single particle model with electrolyte. *J. Electrochem. Soc.* **2019**, *166*, A3693. [CrossRef]

49. Ecker, M.; Gerschler, J.B.; Vogel, J.; Käbitz, S.; Hust, F.; Dechent, P.; Sauer, D.U. Development of a lifetime prediction model for lithium-ion batteries based on extended accelerated aging test data. *J. Power Sources* **2012**, *215*, 248–257. [CrossRef]

50. Todeschini, F.; Onori, S.; Rizzoni, G. An experimentally validated capacity degradation model for Li-ion batteries in PHEVs applications. *IFAC Proc. Vol.* **2012**, *45*, 456–461. [CrossRef]

51. Ecker, M.; Gerschler, J.B.; Vogel, J.; Käbitz, S.; Hust, F.; Dechent, P.; Sauer, D.U. Development of a lifetime prediction model for lithium-ion batteries based on extended accelerated aging test data. *J. Power Sources* **2012**, *215*, 248–257. [CrossRef]

52. Lunz, B.; Yan, Z.; Habchi, R.; Bassil, N.; Salame, C.; Aillerie, M.; Charles, J.P. Evolution of photovoltaic solar modules dark properties after exposition to electrical reverse stress current inducing thermal effect. *Microelectron. Int.* **2014**, *31*, 90–98. [CrossRef]

53. Prada, E.; Oudalov, A.; Ulbig, A.; Andersson, G.; Kirschen, D.S. Modeling of lithium-ion battery degradation for cell life assessment. *IEEE Trans. Smart Grid* **2016**, *9*, 1311–1140. [CrossRef]

54. Ahmed, R.; El Sayed, M.; Arasaratnam, I.; Tjong, J.; Habibi, S. Reduced-order electrochemical model parameters identification and soc estimation for healthy and aged li-ion batteries part i: Parameterization model development for healthy batteries. *IEEE J. Emerg. Sel. Top. Power Electron.* **2014**, *2*, 659–677. [CrossRef]

55. Ahmed, R.; El Sayed, M.; Arasaratnam, I.; Tjong, J.; Habibi, S. Reduced-order electrochemical model parameters estimation and state of charge estimation for healthy and aged Li-ion batteries—Part II: Aged battery model and state of charge estimation. *IEEE J. Emerg. Sel. Top. Power Electron.* **2014**, *2*, 678–690. [CrossRef]

56. Prada, E.; Di Domenico, D.; Creff, Y.; Bernard, J.; Sauvant-Moynot, V.; Huet, F. A simplified electrochemical and thermal aging model of LiFePO4-graphite Li-ion batteries: Power and capacity fade simulations. *J. Electrochem. Soc.* **2013**, *160*, A616. [CrossRef]

57. Guo, J.; Yang, J.; Lin, Z.; Serrano, C.; Cortes, A.M. Impact Analysis of V2G Services on EV Battery Degradation—A Review. In Proceedings of the 2019 IEEE Milan PowerTech, Milan, Italy, 23–27 June 2019; pp. 1–6.

58. Wang, J.; Liu, P.; Hicks-Garner, J.; Sherman, E.; Soukiazian, S.; Verbrugge, M.; Tatari, H.; Musser, J.; Finamore, P. Cycle-life model for graphite-LiFePO4 cells. *J. Power Sources* **2011**, *196*, 3942–3948. [CrossRef]

59. Prada, E.; Di Domenico, D.; Creff, Y.; Bernard, J.; Sauvant-Moynot, V.; Huet, F. A simplified electrochemical and thermal aging model of LiFePO4-graphite Li-ion batteries: Power and capacity fade simulations. *J. Electrochem. Soc.* **2013**, *160*, A616. [CrossRef]

60. Guo, J.; Yang, J.; Lin, Z.; Serrano, C.; Cortes, A.M. Impact Analysis of V2G Services on EV Battery Degradation—A Review. In Proceedings of the 2019 IEEE Milan PowerTech, Milan, Italy, 23–27 June 2019; pp. 1–6.
Energies 2021, 14, 2117

62. Li, Y.; Zhong, S.; Zhong, Q.; Shi, K. Lithium-ion battery state of health monitoring based on ensemble learning. *IEEE Access* 2019, 7, 8754–8762. [CrossRef]

63. Weng, C.; Sun, J.; Peng, H. A unified open-circuit-voltage model of lithium-ion batteries for state-of-charge estimation and state-of-health monitoring. *J. Power Sources* 2014, 258, 228–237. [CrossRef]

64. Safar, I.; Malaric, M.; Bullough, R. Sealed batteries in transient limiting distribution networks-methods of measuring their internal resistance. In Proceedings of the IEEE 12th International Conference on Telecommunications Energy, Orlando, FL, USA, 22–25 October 1990; pp. 458–463.

65. Wang, K.; Gao, F.; Zhu, Y.; Liu, H.; Qi, C.; Yang, K.; Jiao, Q. Internal resistance and heat generation of soft package Li4Ti5O12 battery during charge and discharge. *Energy* 2018, 149, 364–374. [CrossRef]

66. Dubarry, M.; Svoboda, V.; Hwu, R.; Liaw, B.Y. Incremental capacity analysis and close-to-equilibrium OCV measurements to quantify capacity fade in commercial rechargeable lithium batteries. *Electrochem. Solid State Lett.* 2006, 9, A454. [CrossRef]

67. Weng, C.; Feng, X.; Sun, J.; Peng, H. State-of-health monitoring of lithium-ion battery modules and packs via incremental capacity peak tracking. *Appl. Energy* 2016, 180, 360–368. [CrossRef]

68. Pang, X.; Huang, R.; Wen, J.; Shi, Y.; Jia, J.; Zeng, J. A lithium-ion battery RUL prediction method considering the capacity regeneration phenomenon. *Energies* 2019, 12, 2247. [CrossRef]

69. Liu, D.; Pang, J.; Zhou, J.; Peng, Y.; Pecht, M. Prognostics for state of health estimation of lithium-ion batteries based on combination Gaussian process functional regression. *Microelectron. Reliab.* 2013, 53, 832–839. [CrossRef]

70. Olivares, B.E.; Cerda Munoz, M.A.; Orchard, M.E.; Silva, J.F. Particle-Filtering-Based Prognosis Framework for Energy Storage Devices With a Statistical Characterization of State-of-Health Regeneration Phenomena. *IEEE Trans. Instrum. Meas.* 2013, 62, 364–376. [CrossRef]

71. Shi, Y. Modeling, Real-Time Degradation Identification, and Remediation of Lead-Acid Batteries. Ph.D. Thesis, The Pennsylvania State University, State College, PA, USA, 2013.

72. Hawkes, A.; Brett, D.; Brandon, N. Fuel cell micro-CHP techno-economics: Part 2—Model application to consider the economic and environmental impact of stack degradation. *Int. J. Hydrogen Energy* 2009, 34, 9558–9569. [CrossRef]

73. Thangavelautham, J.; Dubowsky, S. On the Catalytic Degradation in Fuel Cell Power Supplies for Long-Life Mobile Field Sensors. *Fuel Cells* 2013, 13, 181–195. [CrossRef]

74. Thangavelautham, J.; Strawser, D.D.; Dubowsky, S. The design of long-life, high-efficiency PEM fuel cell power supplies for low power sensor networks. *Int. J. Hydrogen Energy* 2017, 42, 20277–20296. [CrossRef]

75. Lu, L.; Ouyang, M.; Huang, H.; Pei, P.; Yang, F. A semi-empirical voltage degradation model for a low-pressure proton exchange membrane fuel cell stack under bus city driving cycles. *J. Power Sources* 2007, 164, 306–314. [CrossRef]

76. Kianianmeh, A.; Yang, Q.; Park, S.; Xue, D.; Freiheit, T. Model for the Degradation Performance of a Single-Cell Direct Methanol Fuel Cell under Varying Operational Conditions. *Fuel Cells* 2013, 13, 1005–1017. [CrossRef]

77. Zhang, H.; Williams, M.C. Model for evaluating degradation of high-temperature fuel cell heat engine systems. *Int. J. Hydrogen Energy* 2016, 41, 14230–14238. [CrossRef]

78. Cayan, F.; Pakalapati, S.; Celik, I.; Xu, C.; Zondlo, J. A degradation model for solid oxide fuel cell anodes due to impurities in coal syngas: Part i theory and validation. *Fuel Cells* 2012, 12, 464–473. [CrossRef]

79. Verda, V.; von Spakovskyy, M.R. Development of a detailed planar solid oxide fuel cell computational fluid dynamics model for analyzing cell performance degradation. *J. Fuel Cell Sci. Technol.* 2009, 6. [CrossRef]

80. Zaccaria, V.; Traverso, A.; Tucker, D. A real-time degradation model for hardware in the loop simulation of fuel cell gas turbine hybrid systems. In Proceedings of the ASME Turbo Expo 2015, Montreal, QC, Canada, 15–19 June 2015.

81. Bueno, P. R. Nanoscale origins of super-capacitance phenomena. *J. Power Sources* 2019, 414, 420–434. [CrossRef]

82. Sato, K.; Navarro, D.; Sekizaki, S.; Zoka, Y.; Yorino, N.; Mattausch, H.J.; Miura-Mattausch, M. Prediction of DC-AC Converter Efficiency Degradation due to Device Aging Using a Compact MOSFET-Aging Model. *IEEE Trans. Electron.* 2019. [CrossRef]
90. De Barros, R.C.; da Silveira Brito, E.M.; do Couto Boaventura, W.; Pereira, H.A.; Cupertino, A.F. Methodology for bondwire lifetime evaluation of multifunctional PV inverter during harmonic current compensation. *Int. J. Electr. Power Energy Syst.* 2021, 128, 106711. [CrossRef]

91. De Barros, R.; Brito, E.; Rodrigues, G.G.; Mendes, V.; Cupertino, A.F.; Pereira, H.A. Lifetime evaluation of a multifunctional PV single-phase inverter during harmonic current compensation. *Microelectron. Reliab.* 2018, 88, 1071–1076. [CrossRef]

92. Roy, S.; Hanif, A.; Khan, F. Degradation Detection of Power Switches in a Live Three Phase Inverter using SSTDR Signal Embedded PWM Sequence. In Proceedings of the 2020 IEEE International Reliability Physics Symposium (IRPS), Dallas, TX, USA, 28 April–30 May 2020; pp. 1–7.

93. Chen, C.; Xie, G.; Tang, C.; Sheng, K. Investigation of Gate Degradation Characteristics of AlGaN/GaN HEMTs under PWM Stress. *Adv. Mater. Res.* 2013, 732, 1255–1260. [CrossRef]

94. Fischer, K.; Stalin, T.; Ramberg, H.; Wenske, J.; Wetter, G.; Karlsson, R.; Thiringer, T. Field-experience based root-cause analysis of power-converter failure in wind turbines. *IEEE Trans. Power Electron.* 2014, 30, 2481–2492. [CrossRef]

95. Fischer, K.; Pelka, K.; Bartschat, A.; Tegtmeier, B.; Coronado, D.; Broer, C.; Wenske, J. Reliability of power converters in wind turbines: Exploratory analysis of failure and operating data from a worldwide turbine fleet. *IEEE Trans. Power Electron.* 2018, 34, 6332–6344. [CrossRef]

96. Ma, K.; Liserre, M.; Blaabjerg, F.; Kerekes, T. Thermal loading and lifetime estimation for power device considering mission profiles in wind power converter. *IEEE Trans. Power Electron.* 2014, 30, 590–602. [CrossRef]

97. Yang, Z.; Chai, Y. A survey of fault diagnosis for onshore grid-connected converter in wind energy conversion systems. *Renew. Sustain. Energy Rev.* 2016, 66, 345–359. [CrossRef]

98. Yang, B.B.; Armijo, K.M.; Harrison, R.K.; Thomas, K.E.; Johnson, J.; Taylor, J.M.; Sorensen, N.R. Arc fault risk assessment and degradation model development for photovoltaic connectors. In Proceedings of the 2014 IEEE 40th Photovoltaic Specialist Conference (PVSC), Denver, CO, USA, 8–13 June 2014; pp. 3549–3555.

99. Yang, B.B.; Sorensen, N.R.; Burton, P.D.; Taylor, J.M.; Kilgo, A.C.; Robinson, D.G.; Granata, J.E. Reliability model development for photovoltaic connector lifetime prediction capabilities. In Proceedings of the 2013 IEEE 39th Photovoltaic Specialists Conference (PVSC), Tampa, FL, USA, 16–21 June 2013; pp. 0139–0144.

100. Venkatesh, P.S.; Chandran, V.; Anil, S. Study of Flywheel Energy Storage in a Pure EV Powertrain in a Parallel Hybrid Setup and Development of a Novel Flywheel Design for Regeneration Efficiency Improvement; Technical Report; SAE Technical Paper: New York, NY, USA, 2021.

101. Pullen, K.R. The status and future of flywheel energy storage. *Joule* 2019, 3, 1394–1399. [CrossRef]

102. Hutchinson, A.; Gladwin, D.T. Optimisation of a wind power site through utilisation of flywheel energy storage technology. *Energy Rep.* 2020, 6, 259–265. [CrossRef]