Impact of Battery Aging Model in an Energy Management System for an Isolated Solar Microgrid

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Abstract

Battery aging is an important issue that should be considered in the battery modelling. This is paramount when the battery is part of an isolated microgrid, being this a component with an important investment and replacement cost. In this work, three published aging models are included in a microgrid Energy Management System (EMS) optimization problem. Then, the performance of each model is assessed. To analyze the impact of battery aging models in a microgrid EMS, the real data of components of the microgrid located in Huatacondo in the north of Chile are considered. The results show the economic benefits of including the battery aging model into the EMS. The EMS considering the Bo Zhao aging model has the best performance since the total operating costs is lower (10.61% savings) than the costs obtained on other cases (8.09% savings considering the Drouilhet model and 3.24% considering the Copetti and Chenlo model), as well as a lower loss of battery life overall.

Keywords: Microgrid, Energy Management System, Battery Aging Models, Optimization.

1. Introduction

Microgrids (MGs) can energize a complete community by providing electricity while minimizing energy costs for their consumers. This solution becomes very attractive, since it allows a continuous and safe supply, being able to provide electric power even in the event of a failure in the main distribution system (operating in island mode). In addition, an EMS helps to operate and coordinate a variety of distributed generators (DGs), Energy Storage Systems (EESs), and loads in order to provide high-quality, reliable, sustainable, and environmentally friendly energy in a cost-effective way (Su and Wang, 2012). Therefore, an EMS is an integral part of a MG that ensures an optimal operation.

MGs in general, and particularly when they operate isolated from the main grid, have energy storage systems (ESSs). ESSs can make MGs more cost-effective by storing energy when energy from the main grid is cheap or there is energy surplus from the local DGs (Su and Wang, 2012). ESSs are usually operated to meet the MG electric load, and such operation should consider the factors that accelerate their degradation. This is particularly important on battery based ESSs. The degradation rate on those ESSs is sensitive to operating conditions. In fact, battery temperature, state of charge (SOC), voltage, depth of discharge (DOD), and current magnitude are the most influential and studied aging factors (Baghdadi et al., 2016).

In the specialized literature, there are works related to aging models for EESs. (Berrueta et al., 2018) analyzed the diversity of simulation results obtained with the application of different Li-ion battery aging models, as well as the implications of this diversity in the design of the battery management strategy. (Cardoso et al., 2018) proposed a linear battery aging and degradation model to a multi-energy microgrid sizing model using mixed integer linear programming. (Baghdadi et al., 2016) proposed and validated a calendar and power cycling aging model for two different lithium battery technologies. The model approach is based on Dakin's degradation, which is considered to be a chemical rate approach. Thus, the logarithms of battery capacity fade and resistance increase evolve linearly with time. (Ning et al., 2006) presented a generalized charge–discharge cycle life model based on loss of cyclable lithium ions due to the irreversible solvent reduction reaction.

In this work, we implement three battery aging models in the EMS optimization problem. Then, we analyze and compare the performance of each aging model. Finally, we analyze the economic benefit of considering the aging models in the MG operation optimization.

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The rest of this paper is organized as follows. The battery aging models are introduced in Section 2 and propose the EMS with battery aging models in Section 3. Case study and results are provided in Section 4 and the conclusions are given in Section 5.

2. Battery Aging Models

There are two types of aging that affect the state of health (SoH) of the battery. Cyclic aging corresponds to the deterioration of the battery when completing charge-discharge cycles (Keil et al., 2016). Calendar aging comprises all aging processes that lead to a degradation of a battery cell independent of charge-discharge cycling. In this work, only cyclic aging is considered.

2.1. Model I: Copetti and Chenlo

The Copetti et al., (1993) model estimates the aging of the battery as a function of the current state of charge (SoC) at a given time during operation (see Fig. 1). For this, the model proposes different zones of operation that are linked to a certain aging factor η_{wz} which is measured in $[\%_{SoH}/time]$.

Finally, the SoH is represented as

$$SoH(T) = 1 - [\sum_{t=1}^{T} \eta_{wz} \cdot \delta_t] \qquad \text{(eq. 1)}$$

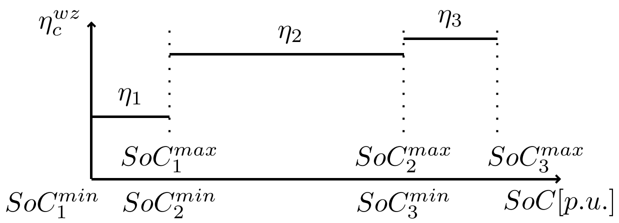

Fig. 1: Operating Zones Depending on the SoC (Copetti and Chenlo aging model)

2.2. Model II: Drouilhet

The Drouilhet and Johnson, (1997) model assumes that the total energy discharged throughout a battery's life is fixed. This parameter, Γ_n , is obtained by applying the following equation:

$$\Gamma_n = L_n D_n C_n \qquad \text{(eq. 2)}$$

where L_n corresponds to the number of nominal cycles that can be obtained from a cell at a certain depth of discharge D_n. C_n corresponds to the nominal capacity of the battery. To estimate the level of aging, the energy drawn in each operation cycle must be accumulated, penalizing operations over the nominal range, such as discharge currents and high depths of discharge (DoD). The following equation shows how to calculate the effective energy discharged from a cycle:

$$d_{eff} = \alpha_{DoD}(DoD) \cdot \alpha_{Id}(I_d) \cdot d_r \qquad \text{(eq. 3)}$$

where d_r corresponds to the actual discharged energy, $\alpha_{Id}Id$ corresponds to the penalty factor for a given discharge current Id, $\alpha_{DoD}(DoD)$ corresponds to the penalty factor for a given DoD and d_{eff} represents the effective value of the energy discharged on the cycle. Finally, the SoH is represented as

$$SoH(T) = 1 - \left[\sum_{t=1}^{T} d_{eff}(t)\right]/\Gamma_n \qquad \text{(eq. 4)}$$

2.3. Model III: Bo Zhao

The Zhao et al., (2013) model is a modification of the Drouilhet model and the Copetti model since it defines different operating zones for the battery. The operating zones are separated according to the SoC of the battery as shown in Fig. 2. Each operating zone introduces a weight, which determines the effective amount of the current that is extracted from the total nominal discharge (same total of the Drouilhet model). To determine the amount of current drawn by the operation of the battery, the following equation is used:

$$d_{ef} = \beta_z d_r \quad \text{(eq. 5)}$$

where d_{ef} represents the effective discharge, β_z corresponds to the weighting of the zone z and d_r corresponds to the actual discharge. To estimate the state of health (SoH) of the battery at a time T, the following equation is used:

$$SoH(T) = 1 - \frac{\sum_{t=1}^{T} d_{ef}(t)}{\Gamma_n} \quad \text{(eq. 6)}$$

where Γ_n was defined in (eq. 2).

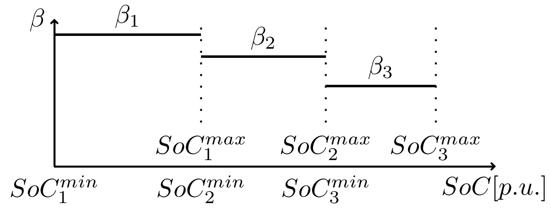

Fig. 2: Operating Zones Depending on the SoC (Bo Zhao aging model)

3. Proposed Energy Management System with Battery Aging Models

In this paper, the EMS proposed in (Palma-Behnke et al., 2013) was used. For the purposes of this work, the aging models described in the previous section are incorporated into the EMS in order to analyze the benefits of considering battery aging models in the MG operation. The EMS minimizes the MG operating costs in a given time horizon, taking the solar generation and the electric load as inputs, and obtaining the power output of the thermal unit and the power delivered/absorbed by the battery bank as outputs. The EMS's formulation corresponds to a mixed integer linear programming (MILP) model. The EMS is effectively solving a unit-commitment (UC) problem with a rolling horizon strategy (UC-RH).

3.1. Objective function

The objective function of the problem addresses the direct and indirect costs incurred in the operation of the system. The objective function is formulated as

$$J = \delta_t \sum_{t=1}^{T} C_{fuel}(t) + \sum_{t=1}^{T} C_s(t) + \delta_t C_{man} T_{man} + \delta_t C_{US} \sum_{t=1}^{T} P_{US}(t) + \delta_t C_{lost} \sum_{t=1}^{T} P_{lost}(t) + C_{inv} SoH_{lost} \quad \text{(eq. 7)}$$

where δ_t is the duration of the time period t, $C_{fuel}(t)$ is the cost function of the thermal unit, $C_s(t)$ is the start-up cost function of the thermal unit, $C_{man}T_{man}$ is the maintenance cost function of the thermal unit, C_{US} is the price for unserved energy, P_{US} is the unserved power in the MG, C_{lost} and P_{lost} are the price and amount of unused power from the energy sources, respectively, C_{inv} is the investment cost of the battery bank, and SoH_{lost} is the loss of useful life of the battery bank according to the models described in section 2.

3.2. Power Balance for the Microgrid

The power balance in the MG must be meet and it is formulated as the constraint

$$P_D(t) + P_I(t) + P_{US}(t) = P_L(t) - P_S(t) - P_{Lost}(t) \quad \text{(eq. 8)}$$

where $P_D(t)$ is the power genetated by thermal unit, $P_I(t)$ is the ESS inverter power, $P_L(t)$ is the electrical load and $P_S(t)$ is the available solar power. Additional constraints for the optimization problem are $P_{US}(t) \geq 0$ and $P_{Lost}(t) \leq 0$.

3.3. Constraints of Drouilhet Aging Model

Drouilhet's aging model is a nonlinear function, therefore the nonconvex function can be approximated by n_d piecewise linear segments (see Fig. 3) to be incorporated into the optimization problem.

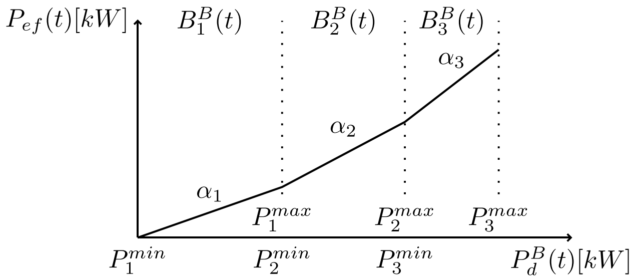

Fig. 3: Drouilhet Aging Model Penalty Curve

The following restriction imposes that only one of the model segments will be active at each interval of the optimization horizon.

$$P_d^{min} B_d^B(t) \leq P_d^B(t) \leq P_d^{max} B_d^B(t) \quad \text{(eq. 9)}$$

Where $P_d^B(t)$ is an auxiliary variable that helps determine the discharge power of the battery bank, $B_d^B(t)$ is a binary auxiliary variable that indicates which section of the model will be active and when the battery bank will be discharging, parameters P_d^{min} and P_d^{max} correspond to the lower and upper limits of section d of the model. The restrictions that determine the relationship between auxiliary variables $P_d^B(t)$ and $B_d^B(t)$ with their respective real variables are shown below.

$$P_B^+(t) = \sum_{d=1}^{n_d} P_d^B(t) \quad \text{(eq. 8)}$$

$$B_B^+(t) = \sum_{d=1}^{n_d} B_d^B(t) \quad \text{(eq. 9)}$$

To determine the effective power, the following equation is applied.

$$P_B^{ef}(t) = \sum_{d=1}^{n_d} \alpha_d P_d^B(t) + \beta_d B_d^B(t) \quad \text{(eq. 10)}$$

With this last restriction we can calculate the loss of useful life on the optimization horizon.

$$SOH_{lost} = \frac{\sum_{t=1}^{T} P_B^{ef}(t)}{\Gamma_n} \quad \text{(eq. 11)}$$

Where Γ_n corresponds to the total nominal discharge defined in (eq. 2).

3.4. Constraints of Copetti Aging Model

The auxiliary variable $SoC_c(t)$ and the binary auxiliary variable $B_c^{soc}(t)$ are introduced to determine which weighter to use at the indicated time.

$$SoC_c^{min} B_c^{soc}(t) \leq SoC_c(t) \leq SoC_c^{max} B_c^{soc}(t) \quad \text{(eq. 12)}$$

Where SoC_c^{min} and SoC_c^{max} represent the lower and upper limits of the operation zone c. The relationship between the auxiliary variable SoCc(t) and the original variable SoC(t) is determined by the constraint.

$$SoC(t) = \sum_{c=1}^{n_c} SoC_c(t) \quad \text{(eq. 13)}$$

Where n_c corresponds to the number of operating zones. In addition, since the weighter must be active in only one operating zone by interval, the following restriction is incorporated.

$$\sum_{c=1}^{n_c} B_c^{soc}(t) = 1 \quad \text{(eq. 14)}$$

The binary auxiliary variables of the battery bank $B_c^+(t)$ and $B_c^-(t)$ represent charging and discharging respectively. These variables are related to the original variables according to the following constraints.

$$B_B^+(t) = \sum_{c=1}^{n_c} B_c^+(t) \quad \text{(eq. 15)}$$

$$B_B^-(t) = \sum_{c=1}^{n_c} B_c^-(t) \quad \text{(eq. 16)}$$

The following constraints force auxiliary variables $B_c^+(t)$ and $B_c^-(t)$ to be set to 0 when they are not in the corresponding operating zone, but these restrictions have the flexibility to operate (set to 1) or not to operate when they are in the corresponding operating zone.

$$B_c^+(t) \le B_c^{soc}(t) \qquad \text{(eq. 17)}$$

$$B_c^-(t) \le B_c^{soc}(t) \qquad \text{(eq. 18)}$$

The following equations can be used to calculate the loss of state of health by interval and the loss of state of health on the optimization horizon.

$$SoH_{lost}^+(t) = \sum_{c=1}^{n_c} \eta_c^{wz} B_c^+(t) \qquad \text{(eq. 19)}$$

$$SoH_{lost}^-(t) = \sum_{c=1}^{n_c} \eta_c^{wz} B_c^-(t) \qquad \text{(eq. 20)}$$

$$SoH_{lost}(t) = \sum_{c=1}^{n_c} SoH_{lost}^+(t) + SoH_{lost}^-(t) \qquad \text{(eq. 21)}$$

3.5. Constraints of Bo Zhao Aging Model

The auxiliary variable $SoC_z(t)$ and the binary auxiliary variable $B_z^{soc}(t)$ are introduced to determine the operating zone.

$$SoC_z^{min} B_z^{soc}(t) \le SoC_z(t) \le SoC_z^{max} B_z^{soc}(t) \qquad \text{(eq. 22)}$$

Where SoC_z^{min} and SoC_z^{max} are the lower and upper limits of the operating zone z. The relationship between the auxiliary variable $SoC_z(t)$ and the original variable $SoC(t)$ is determined by the following constraint.

$$SoC(t) = \sum_{z=1}^{n_z} SoC_z(t) \qquad \text{(eq. 23)}$$

Where n_z corresponds to the number of operating zones. The binary variable $B_z^{soc}(t)$ is set so that only one of the operating zones is active in each time interval.

$$\sum_{z=1}^{n_z} B_z^{soc}(t) = 1 \qquad \text{(eq. 24)}$$

The new auxiliary variable $P_z^+(t)$ is incorporated, which is activated in the operation area according to binary variable $B_z^{soc}(t)$.

$$0 \le P_z^+(t) \le P_B^{max} B_z^{soc}(t) \qquad \text{(eq. 25)}$$

The relationship between the auxiliary variable $P_z^+(t)$ and the original variable is given by the following equation.

$$P_B^+(t) = \sum_{z=1}^{n_z} P_z^+\,(t) \qquad \text{(eq. 26)}$$

The effective power in each interval is calculated with the following equation.

$$P_B^{ef}(t) = \sum_{z=1}^{n_z} \beta_z P_z^+\,(t) \qquad \text{(eq. 27)}$$

Where β_z corresponds to the value of the weight in the operating area z. The loss of useful life on the optimization horizon is calculated using the following constraint.

$$SoH_{lost} = \frac{\sum_{t=1}^{T} P_B^{ef}(t)}{\Gamma_n} \qquad \text{(eq. 28)}$$

Where Γ_n corresponds to the total nominal discharge defined in (eq. 2).

4. Study Case and Results

To analyze the impact of battery aging models in an MG EMS, we considered the real data of components of the MG located in Huatacondo in the north of Chile (Palma-Behnke et al., 2013), the MG historic operation and the technical information of the battery bank to obtain the parameters used in the aging models.

The following results were obtained for a time horizon of 24 hours and a sampling time of 60 minutes, for a period of 31 days. To perform the unit-commitment, the rolling horizon method is used. This method considers the feedback of variables with a certain level of uncertainty (electric charge, maximum available solar power, maximum available wind power, etc.) in each iteration. This requires recalculating the unit-commitment each time a new value is obtained from these variables.

The three models generate an impact on the final operation of the MG, reducing total costs in the long term. This reduction is mainly due to the optimal use of the battery bank made by the EMS. The diesel generator reduces its operation, and this causes a reduction in battery activity. The results of the injected energy by the diesel generator, photovoltaic and battery bank are shown in Fig. 4.

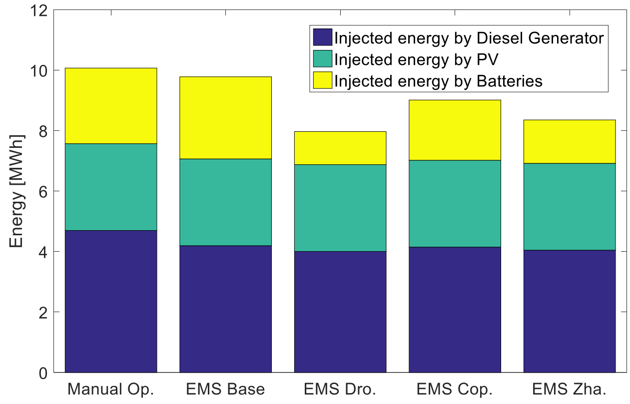

Fig. 4: Injected Energy by Diesel Generator, Photovoltaic and Battery Bank

Manual operation refers to the manual activation of the diesel generator, which is how the Huatacondo MG currently operates. From the previous results the following is noted:

- The Diesel Generator supplies less energy when the EMS considers aging models as it does not charge the batteries very often. Therefore, it reduces the aging of the batteries which is reflected in the decrease of the total costs of the system.
- The Diesel Generator supplies more energy when the EMS does not consider aging models (EMS base). However, the total fuel cost was lower. This is because the EMS base operates the diesel generator at a higher power output (and therefore more efficient) than the EMS with aging models. The thermal unit is most efficient when it operates near its maximum capacity (with a variable cost of 173 [CLP/kWh]) while, when it operates near its minimum capacity, the unit consumes more fuel and the variable cost increases (310 [CLP/kWh]).

Fig. 5 shows the power curves of the battery bank operation for the EMS with the three different aging models and the base EMS without any aging models. Fig. 6 summarizes the main economic results of operating MG with the various aging models of the battery bank. In this figure, the direct costs C_{dir} correspond to the fuel consumed by the diesel generator, and the indirect costs C_{ind} correspond to the costs of energy not supplied, costs of spillage and cost for use of the battery bank.

Fig. 6 shows that, regardless of the model considered, the savings obtained by optimizing the use of the battery bank is considerable. The model that stands out is mainly that of Bo Zhao, which presents a saving of 10.61% in the total costs. It is emphasized that indirect costs are not identical in the EMS base, since these costs were calculated *a posteriori* using each of the aging models, but without incorporating this cost in the objective function of the optimization problem.

In terms of extending the useful life of the battery bank, the Drouilhet model is the one that delivers the best results. This model achieves a lower loss of useful life, however, to supply the energy required by the MG the diesel generator uses more fuel and the total cost increases.

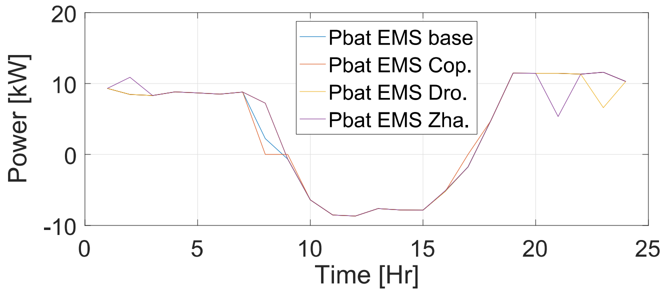

Fig. 5: Power Delivered by the Battery Bank

Results (UC-RH)				
	C_{dir} [CLP]	C_{ind} [CLP]	C_{tot} [CLP]	SoH_{lost}
Manual Op.	1.421.071	268.445	1.689.516	2,68%
EMS Base (mod. Dro.)	884.865	338.815	1.223.681	3,38%
EMS Base (mod. Cop.)	881.722	305.144	1.186.866	3,05%
EMS Base (mod. Zha.)	880.901	352.335	1.233.236	3.52%
EMS mod. Dro.	989.143	135.526	1.124.670	1.35%
EMS mod. Cop.	936.495	211.853	1.148.349	2.07%
EMS mod. Zha.	962.684	139.680	1.102.365	1.39%

Fig. 6: Results of the Total Operating Costs and Loss of Useful Life of the Battery Bank

5. Conclusions

In this work, three published battery aging models were implemented and compared. These models were incorporated into an EMS optimization problem to obtain the operation results of a MG. To analyze the impact of battery aging models in a MG EMS, the real data of components of the MG located in Huatacondo in the north of Chile were considered. The results showed the economic benefit of considering the battery aging models into the optimization problem for the economic dispatch of the MG. The EMS considering the Bo Zhao aging model has the best performance since the total operating costs is lower (10.61% savings) than the costs obtained on other cases (8.09% savings considering the Drouilhet model and 3.24% considering the Copetti and Chenlo model), as well as a lower loss of battery life overall.

6. Acknowledgments

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