doi:10.20944/preprints201610.0003.v1

Peer-reviewed version available at *Batteries* **2017**, *3*, 10; doi:10.3390/batteries3010010

Article

2nd life batteries on a gas turbine power plant to provide area regulation services.

Lluc Canals Casals [1]* and Beatriz Amante García [1]

[1] Universitat Politècnica de Catalunya; lluc.canalsl@upc.edu
* Correspondence: lluc.canalsl@upc.edu; Tel.: +34 93 7398154

Abstract: Batteries are called to be part of the electricity grid by providing ancillary services. Area regulation services seem to provide substantial revenues and profit. But Li-ion batteries are still too expensive to enter widely into this market. On the other hand, electric vehicle batteries are considered inappropriate for traction purposes when they reached a state of health of 80%. The reuse of these batteries offers affordable batteries for second life stationary applications. This study analyzes how batteries may provide services to a gas turbine cogeneration power plant and how long these batteries may last under different loads.

Keywords: Aging model; Lithium ion batteries; Second life applications, Area regulation

1. Introduction

The entrance of the electric vehicle, growing industry and world energy demand together with an environmental consciousness rise are forcing a transformation on the electricity grid in many countries. New electricity services are under study for their expected economic or functional benefits, such as peak shaving, load leveling, area regulation, transmission deferral, renewable firming among others [1] [2] [3], [4], as well as new concepts like distributed generation [5] or the need for smart grid implementation [6]. Moreover, batteries seem to be able to provide optimal responses to these services. In particular, Lithium-ion batteries are the ones having a wider range of applications [7]. However, Lithium-ion batteries are still too expensive to be massively deployed on stationary applications, which delay their entrance.

On the other hand, electric vehicle (EV) batteries are expected to be inappropriate for traction purposes after they reach an 80% of their State of Health (SoH) [8]. Having still an important amount of functional capacity, these batteries may be used on the aforementioned stationary applications at much lower cost, giving them a second life.

2nd life batteries find in electricity grid quality services an important market with profitable businesses. In fact area or frequency regulation, which increases or decreases the energy injected to the grid to instantly balance generation and demand or maintain the frequency between the working limits, seems to be the most promising [9].

Turbine generators often provide area and frequency regulation services due to their quite a fast response. Although most of times hydraulic turbines provide this service because of their low operation cost, as they have no need to buy any fuel, season and weather conditions give the opportunity to participate into the business to gas turbines or co-generation plants. Wanting to have a higher participation in the electricity regulation market, gas turbines may take profit of 2nd life batteries to become more competitive.

There are several aspects to take into account when repurposing an EV battery, such as communications, chemistry and cell type among others [10]. Additionally, there are different ways to affront remanufacturing processes, such as Direct re-use [11], [12] or module and cell dismantling [13]. Finally in order to determine which battery is best for each application, knowing that batteries age differently according to their use and load, it is important to estimate the Rest of Useful Life (RUL) of 2nd life batteries.

Peer-reviewed version available at *Batteries* **2017**, *3*, 10; doi:10.3390/batteries3010010

To estimate RUL, the first thing to do is to determine the battery SoH when returned from a car. There are plenty of methods to estimate SoH of batteries ranging from manual measurements of capacity to fully automated onboard supervision of various battery parameters [14]. In this study we expect to obtain SoH directly from the EV, as most of them have some algorithm implemented to estimate it. This study considers that batteries will have an 80% SoH, although there are some critical voices to this limit, as many drivers may continue using EVs well beyond it [15]. In fact, this generally accepted value for the battery EoL on EVs is the beginning of the second life.

Secondly, an aging model estimates battery degradation. However, as reported by Devie & Dubarry [16], most of the studies use inaccurate aging models. In fact, many use basic models based on the expected number of cycles, the accumulated Ah throughput or on expected lifetime adjusted by temperature or, in best cases, with more than one factor. This study takes advantage of a previous work [17] that developed an aging equivalent electric circuit model based on State of Charge (SoC) or Voltage (V), Depth of Discharge (DoD), Current or intensity (C-rate), Temperature (T), Ah thorughput and time (t) or calendar aging.

In summary, having the initial conditions of the battery SoH for the 2nd life, this article proceeds to estimate the RUL of an EV reused battery by means of an equivalent electric circuit for the specific case of area regulation. This study works with direct re-used 24kWh batteries from a single EV installed on a 500 kW gas turbine power plant specifically dedicated to area regulation services.

2. Results

In the first scenario, where turbines work under a softened load resulting from the average demand of set points during the last minute, Figure 1 presents the resulting working loads of gas turbines (orange) and batteries (black), which together follow the set points (blue) given by the electricity grid operator.

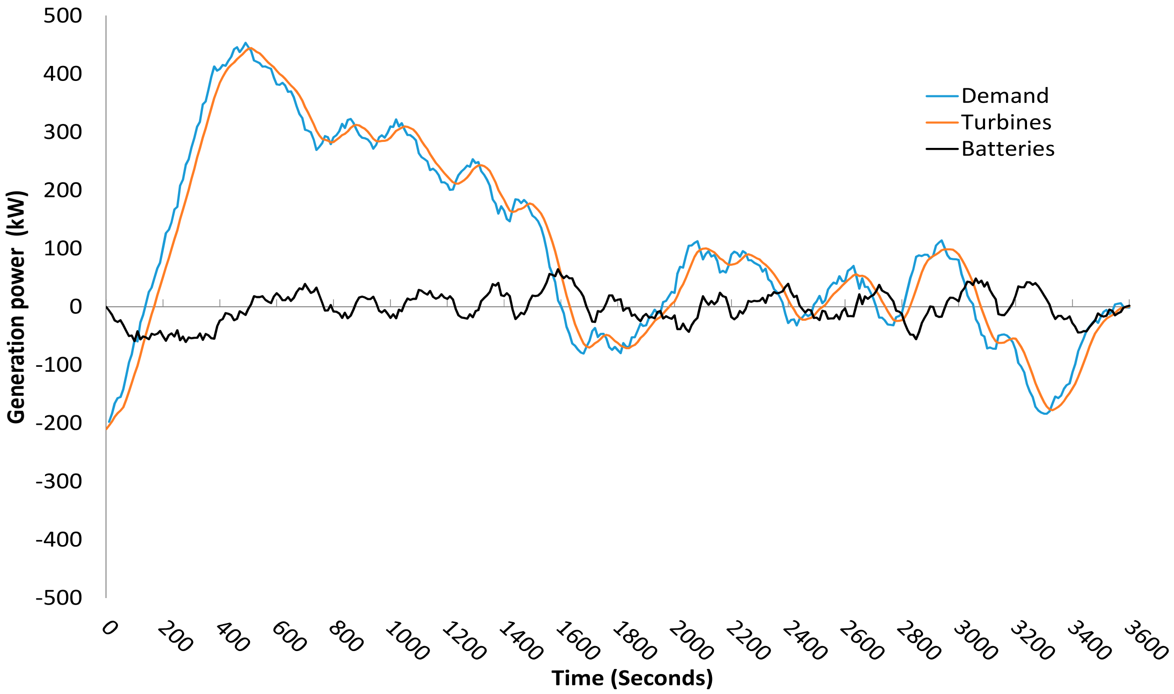

Figure 1: Working load of turbines and batteries in contrast to demand for the first scenario.

On the other hand, Figure 2 presents the working load of turbines (grey) and batteries (black) resulting from the second scenario, where turbines work under constant power or constant acceleration/deceleration.

Peer-reviewed version available at *Batteries* **2017**, *3*, 10; doi:10.3390/batteries3010010

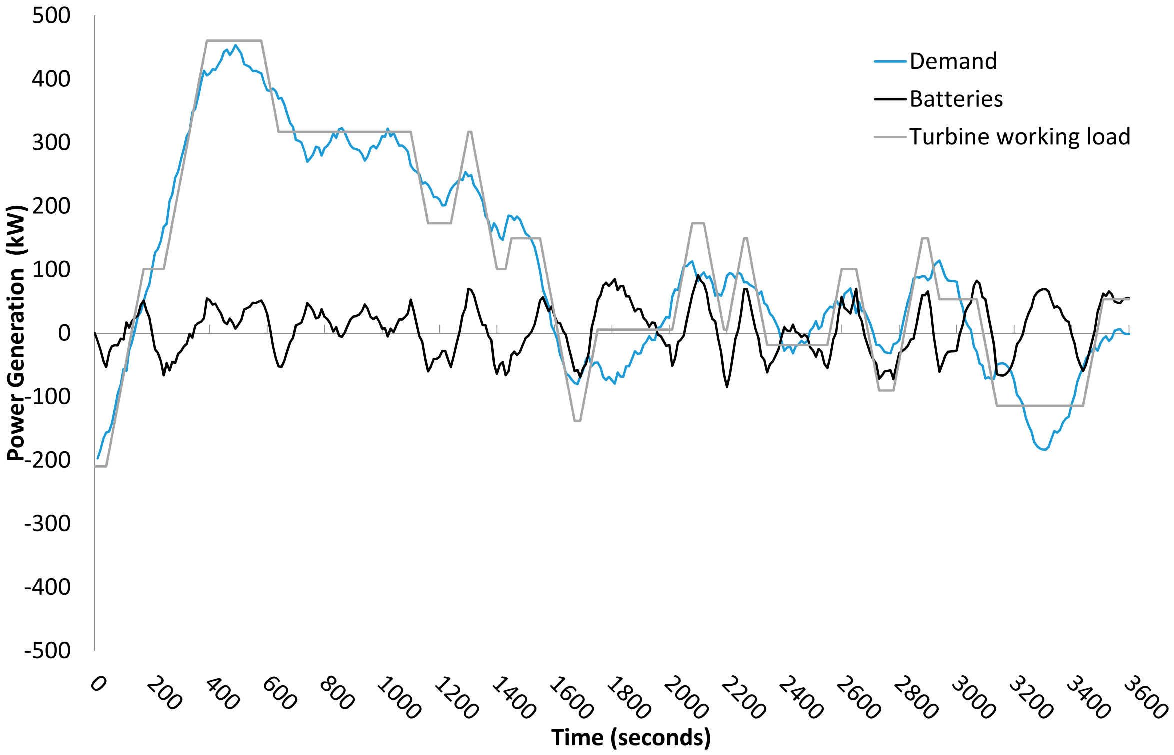

Figure 2: Working load of turbines and batteries in contrast to demand for the second scenario.

Notice that the second scenario demands more energy exchange (20 kWh charge and discharge) and higher power rates to batteries than the first scenario, which finishes around 11 kWh charge and discharge per cycle. This will certainly have an effect on the aging evolution.

Considering the extreme load conditions, 24 and 22cycles per day in the first and second scenario respectively, it is not surprising that batteries age fast. Figure 3 shows the aging or SoH evolution against the number of cycles for the first scenario. These results indicate that the EV battery installed to provide softer working changes to turbines lasts over 2000 cycles before reaching its EoL on this second life application. This EoL occurs when the battery cannot provide all the energy needed to fulfill the demand set points given by the electricity regulator. That is, the battery reaches its minimum SoC conditions while the systems still demands energy. This EoL corresponds to a 0.4653% SoH (Figure 3) and it is reached after 84 days working nonstop.

doi:10.20944/preprints201610.0003.v1

Peer-reviewed version available at *Batteries* **2017**, *3*, 10; doi:10.3390/batteries3010010

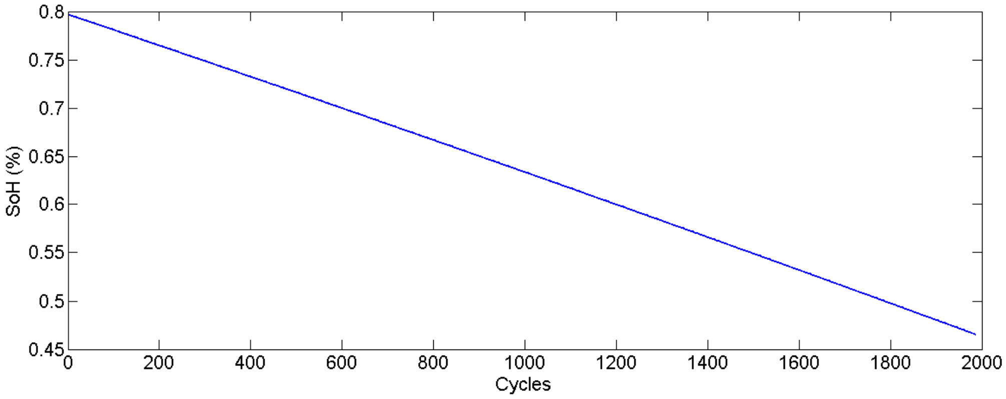

Figure 3: Aging evolution of 2nd life EV batteries under the 1 minute time lag.

Figure 4 presents SoC evolution and Current input of the system in one of the last cycles of the battery running the first scenario. Notice that minimum SoC is close to 10% while maximum SoC is near 95%. These are the working limits fixed by the car manufacturer to ensure battery lifespan during its first life. These limitations cannot be modified for the 2nd life if we expect car manufacturers to keep warranties on them. SoC range from reused batteries at the beginning of the 2nd life application, when they had an 80% SoH, went from 95 to 40%.

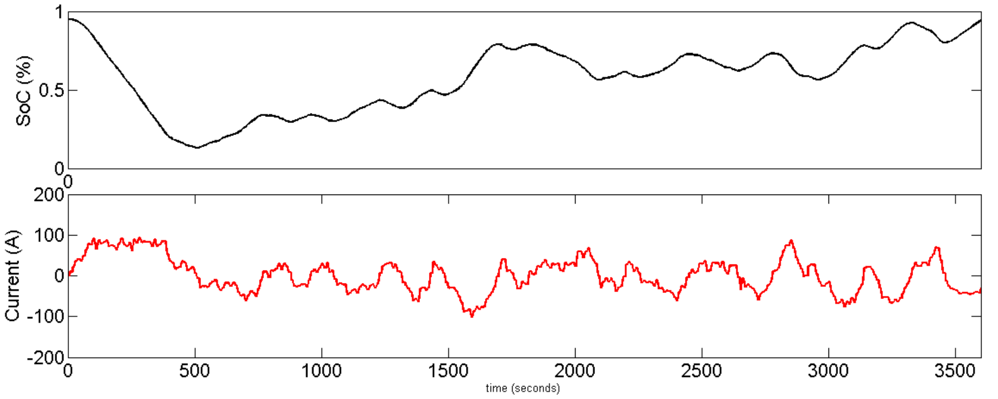

Figure 4: Battery SoC evolution (Up) in one of the last simulated cycles following the first scenario input current (Down).

Finally, Figure 5 presents the evolution of SoH or aging for the second scenario. Having higher power and energy demand to the battery, the EoL in this scenario corresponds to 0.5143 % SoH, which is a 5% higher than the first scenario. Moreover, Figure 5 shows that it takes less than 800 cycles to reach this EoL, which correspond to only 36 days. This means that, under the second scenario, battery's lifespan is less than half the lifespan from the first scenario.

Peer-reviewed version available at *Batteries* **2017**, *3*, 10; doi:10.3390/batteries3010010

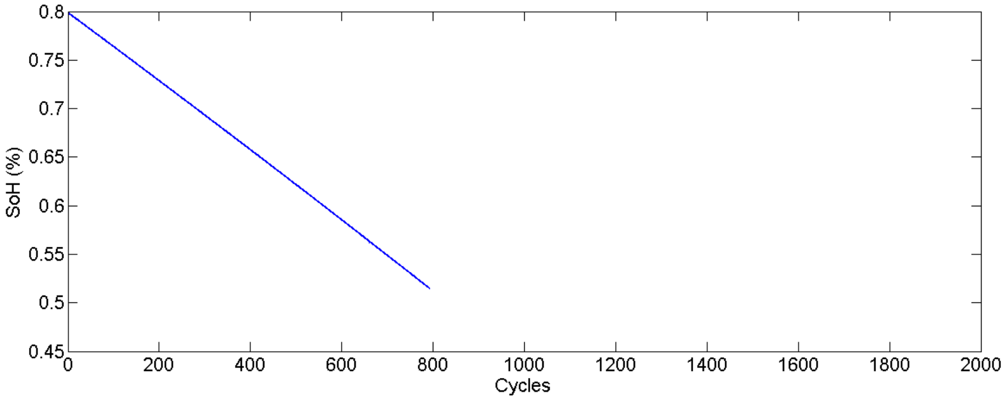

Figure 5: Aging evolution **of** 2nd life EV batteries following the 2nd scenario load.

3. Discussion

Based on the results in section 2, we observe that, effectively, battery aging is more aggressive on the second scenario, which does 800 cycles during 35 days in comparison to the almost 2000 cycles and 84 days of work. These results do not seem bad when regarding the number of cycles batteries can do, but they are alarming in terms of days. If batteries should work under these load conditions during these short periods, they will certainly not enter into the market.

However, as expressed in the methodology section regarding the study limitations, a non-stop continuous working condition is rare for gas turbine plants in the area regulation market. Thus, if the number of cycles per day reduces significantly, battery lifespan will increase accordingly. In fact, 800 and 2000 cycles are good-enough results.

Furthermore, notice that the EoL estimated for these two 2nd life applications falls beyond the 60% SoH. There are not many studies on EV cells and batteries that cycle batteries until such low SoH. In fact, most of them finish when the battery reaches the 80% SoH. Therefore, it is possible that other unexpected circumstances will occur beyond this limit, such as the aging knee phenomena.

Additionally, this study assumes that there is only one reused EV battery to give support to the whole gas turbine system. Putting more batteries in series or parallel, thus multiplying their power and capacity, would significantly improve these aging results, as some of the aging factors would reduce their impact, such as DoD, C-rate and Ah throughput. Howbeit, investments would increase in consequence, forcing to perform a deep economic study.

4. Materials and Methods

Generally, when a system enters into the area regulation market, the electricity grid operator examines it and fixes its maximum working load conditions and ramps up or down so the operator will not demand something that the facility cannot provide. In Spain, the market tendering fixes which system provides or reduces the energy into the grid 15 minutes prior to its incorporation, leaving not much time to gas turbines to react. Each candidate offers a basic range of energy and a capability of 58% to increase and 42% to decrease it during one-hour periods and the operator adapts the set data points to the proposed bid.

This study bases its calculations on real demand Area regulation data from the Spanish operator “Red Eléctrica” given to a gas-turbine power plant. This power plant has several 50kW gas turbines able to provide 0,5 MW up/down. Figure 6 presents the set points for one-hour period that the plant should follow in order to participate in the Area regulation market. Notice that these set points actualize every 4 seconds, forcing the system to rapidly adapt to it.

Peer-reviewed version available at *Batteries* **2017**, *3*, 10; doi:10.3390/batteries3010010

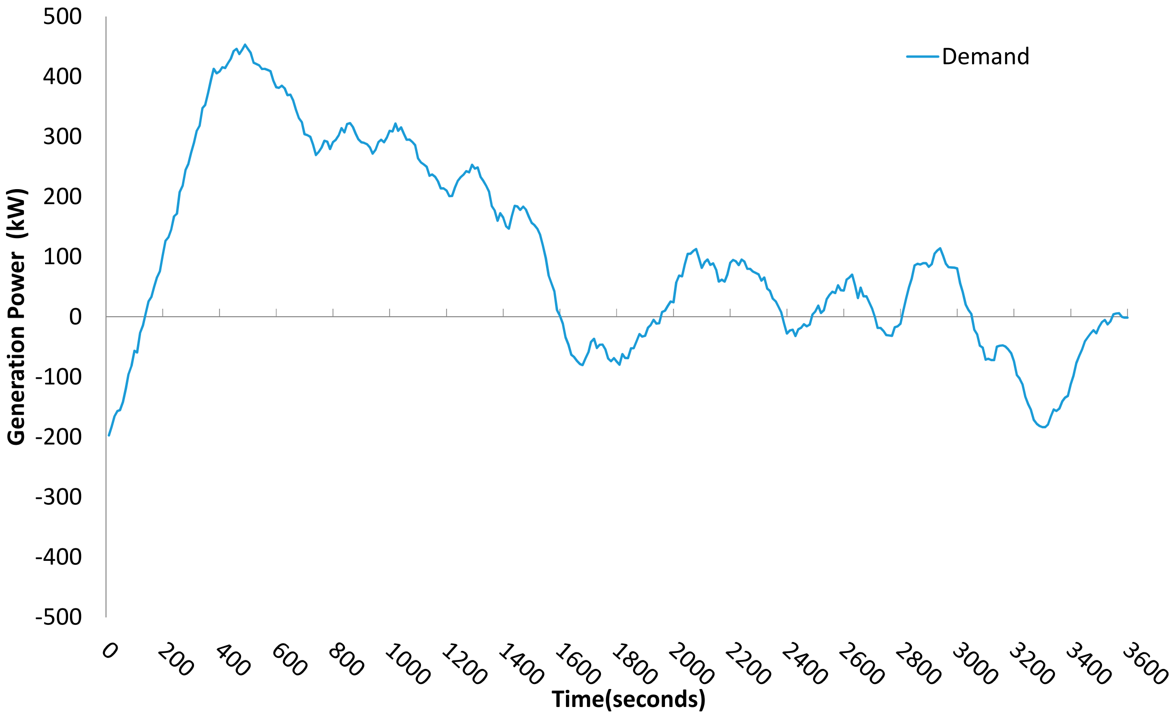

Figure 6: Set points fixed by the electricity grid operator that the generation plant should follow.

Trying to upgrade this facility to a more competitive one, this study presents the possibility to improve the plant response and functionality by adding one 2nd life EV battery to the system, knowing that batteries have better time responses than gas turbines [18]. This study presents two preliminary scenarios:

- Scenario one. This scenario tries to minimize complications caused by fluctuations from the transitory states between set points [19]. This softening is achieved by transferring to turbines a recalculated working set point based on the average power demand during the last minute. In consequence, the response of turbines is softer and displaced one minute while batteries provide or consume the lack or excess of energy caused by the time lapse. Figure 1 in the results sections presents the resulting load curves for turbines and the 2nd life battery.
- Scenario two. Turbines work at constant speed or under constant acceleration/deceleration rate fixed at 2/3 of the maximum capacity of the system, eliminating the inefficiencies on adjusting consumption to demand and improving turbine's lifespan by never working close to maximum acceleration rates. Again, batteries are responsible to provide or accumulate the necessary energy to adapt turbine's electricity generation to set points required by the grid operator. The maximum sustained power that batteries may offer (60 kW per battery) marks the maximum difference between the operator's set point and the working conditions of turbines. Thus, when this difference is above the limit, turbines will ramp up, stabilize or reduce its velocity according to the previous working stage. That is, if turbines where working at constant speed and the battery needs to provide more than 60 kW, turbines will begin to accelerate their working speed. On the other hand, if battery charge gets over this limit, turbines will start to decrease their speed. Figure 2 in the results section clarifies these explanations.

4.1. Second life EV battery aging model

The second part of this study analyzes the 2nd life EV battery aging evolution under both scenarios. To do so, we take advantage of a previous work were we defined an aging model based on an electric equivalent circuit that simulates the battery behavior [17]. This aging model is based on an NMC battery.

This model takes into account calendar and cycling aging of batteries and most of the known factors affecting batteries’ degradation. This factors are: Temperature (T), Depth of discharge (DoD), State of charge (SoC) and current or intensity (C-rate) [20], [21], which are incorporated in the aging model following equations (1) and (2).

$$C_{loss\_cal} = f(V, T, t) \tag{1}$$

$$C_{loss\_cyc} = f(I, V, DoD, T, t) \tag{2}$$

Calendar aging follows an Arrhenius like curve related to voltage and temperature, which is defined by equation (3)

$$C_{loss\_cal} = (\beta_1 + \beta_2 \cdot V) \cdot 10^6 \cdot e^{\frac{\beta_3}{T}} \cdot \sqrt{t} \tag{3}$$

This model uses voltage to represent the aging effect of SoC, as indicated by equations (1) and (2) and supported by literature [22], [23]. In particular, its impact on cycling follows the expression from equation (4).

$$V_{ef} = \theta_4 \cdot V + \theta_5 \tag{4}$$

Regarding the cycling conditions, DoD and C-rate affect battery aging following a logarithmic and second-degree polynomial expression respectively [24], [25] represented by equations (5) and (6),

$$I_{ef} = \theta_1 \cdot I^2 + \theta_2 \cdot I + \theta_3 \tag{5}$$

$$DoD_{ef} = \frac{Log_{10}(DoD)}{2} \tag{6}$$

Finally, temperature’s effect on aging while cycling is related to the base case degradation, according to equation (7).

$$T_{ef} = \frac{e^{\frac{\theta_6}{T}}}{e^{\frac{\theta_6}{298}}} \tag{7}$$

In fact, equations (3-7) represent the effect of these factors (V, C-rate, DoD and T) against its base case degradation, which is the capacity loss occurring under continuous cycling at 25 ºC, 1C, 100%DoD and 50% average SoC. Moreover, parameters β_1, β_2, β_3, θ_1, θ_2, θ_3, θ_4, θ_5 and θ_6 are representative of one battery type only and may substantially change from one model to another.

This aging model uses current in and out from the battery to simulate the behaviour and acquisition of all the aforementioned parameters. Thus, to estimate the battery RUL under both scenarios, we extracted the current profile from the power load required to the battery resulting from both system upgrades.

4.2. Study limitations

This study presents the first approach to battery lifespan estimation for the application on area regulation considering all the known aging factors. However, it has several limitations to notice.

First, it takes only one-hour cycle to simulate the whole working conditions of the system along time. This is unlikely to happen, as area regulation changes constantly and the demand curve will never be the same. Nonetheless, it seemed a good assumption for first results estimations. Future works will have to deal with this variability, where more than one battery will be certainly needed. Moreover, in this study, the system is assumed to be working 24 h a day all days of the year, which is also difficult to occur. This would mean that the system is always winning the auctions, which is most unprovable.

Batteries could directly participate into the Area regulation market absorbing or providing energy to the grid when needed. However, area regulation has a tendency to have more demand increase than decrease, in a relation of 58/42. This would mean that, after some cycles, batteries should recharge somehow to be capable again of running the system. Moreover, the amount of batteries needed to provide 0,5 MW power and enormous quantity of energy represent a lot of batteries stacked together, needing deep economic business and cost analysis. This is also something to discuss in future works.

Turbine's upgrade scenarios may be improved incorporating predictive tools and other close to the problem reality of turbine's regulation. However, we assumed that the two scenarios presented showed already the interest of batteries giving support to turbines on area regulation.

Finally, the aging model does not include a variability or sensibility analysis (as not all cells in a battery or between batteries) age exactly following the same curve, some age faster and others slower. Moreover, the aging model does not consider the "aging knee", moment in which the aging mechanisms change and battery degradation may substantially accelerate [26].

Acknowledgments: The authors would like to thank the Universitat Politècnica de Catalunya (UPC) and the ReViBE project TEC2015-63899-C3-1-R (MINECO/FEDER) funded by the Spanish government.

Author Contributions: Beatriz Amante García prepared and obtained the raw data from Area Regulation and suggested system upgrades. Lluc Canals Casals prepared and ran the simulations. They both wrote the paper.

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

References

1. Denholm, P.; Jorgenson, J.; Jenkin, T.; Palchak, D.; Kirby, B.; Malley, M. O. The Value of Energy Storage for Grid Applications The Value of Energy Storage for Grid Applications. **2013**.
2. Eyer, J.; Corey, G. *Energy Storage for the Electricity Grid*: *Benefits and Market Potential Assessment Guide A Study for the DOE Energy Storage Systems Program*; Albuquerque, 2010.
3. Rastler, D. *Electricity Energy Storage Technology Options*; 2010.
4. Culver, W. J. High-Value Energy Storage for the Grid: A Multi-Dimensional Look. *Electr. J.* **2010**, *23*, 59–71.
5. El-Khattam, W.; Salama, M. M. A. Distributed generation technologies, definitions and benefits. *Electr. Power Syst. Res.* **2004**, *71*, 119–128.
6. Güngör, V. C.; Sahin, D.; Kocak, T.; Ergüt, S.; Buccella, C.; Member, S.; Cecati, C.; Hancke, G. P. Smart Grid Technologies®: Communication Technologies and Standards. *IEEE Trans. Ind. INFORMATICS* **2011**, *7*, 529–539.
7. Dunn, B.; Kamath, H.; Tarascon, J.-M. Electrical energy storage for the grid: a battery of choices. *Science* **2011**, *334*, 928–35.
8. Wolfs, P. An Economic Assessment of " Second Use " Lithium- Ion Batteries for Grid Support. In *Universities Power Engineering Conference (AUPEC), 2010 20th Australasian*; Christchurch, 2010.
9. Neubauer, J.; Pesaran, A. The ability of battery second use strategies to impact plug-in electric vehicle prices and serve utility energy storage applications. *J. Power Sources* **2011**, *196*, 10351–10358.
10. Canals Casals, L.; Amante García, B. Assessing electric vehicles battery second life remanufacture and management. *J. Green Eng.* **2016**, *6*, 77–98.
11. Gohla-Neudecker, B.; Bowler, M.; Mohr, S. Battery 2nd life: Leveraging the sustainability potential of EVs and renewable energy grid integration. In *5th International Conference on Clean Electrical Power: Renewable Energy Resources Impact, ICCEP 2015*; 2015; pp. 311–318.
12. Cruz Gibert, H.; Cruz Zambrano, M.; Canals Casals, L.; Castella Daga, S.; Diaz Pinos, P. Sunbatt: Use of a Second Life Battery System from PHEV in Stationary Applications. In *Smart City Expo World Congress*; Barcelona, 2015.
13. Ramoni, M. O.; Zhang, H. C. End-of-life (EOL) issues and options for electric vehicle batteries. *Clean Technol. Environ. Policy* **2013**, *15*, 881–891.

14. Goebel, K.; Saha, B.; Saxena, A.; Celaya, J. R.; Christophersen, J. P. Prognostics in Battery Health Management. *IEEE Instrum. Meas. Mag.* **2008**, 33–40.
15. Saxena, S.; Le Floch, C.; Macdonald, J.; Moura, S. Quantifying EV battery end-of-life through analysis of travel needs with vehicle powertrain models. *J. Power Sources* **2015**, *282*, 265–276.
16. Devie, A.; Dubarry, M. Durability and Reliability of Electric Vehicle Batteries under Electric Utility Grid Operations. Part 1: Cell-to-Cell Variations and Preliminary Testing. *Batteries* **2016**, *2*, 28.
17. Canals Casals, L.; Amante García, B.; González Benítez, M. Modelo de envejecimiento de baterías de vehículo eléctrico reutilizadas para aplicaciones estacionárias. In *XIX International congress on project management and engineering*; Granada, 2015.
18. Lian, B.; Yu, D.; Wang, C.; Le Blond, S.; Dunn, R. W. Investigation of energy storage and open cycle gas turbine for load frequency regulation. In *49th International Universities Power Engineering Conference (UPEC)*; 2014; pp. 1–6.
19. Balamurugan, S.; Janarthanan, N.; Chandrakala, K. R. M. V. Small and large signal modeling of heavy duty gas turbine plant for load frequency control. *Int. J. Electr. Power Energy Syst.* **2016**, *79*, 84–88.
20. Vetter, J.; Nov, P.; Wagner, M. R. R.; Veit, C.; Novák, P.; Möller, K.-C.; Besenhard, J. O.; Winter, M.; Wohlfahrt-Mehrens, M.; Vogler, C.; Hammouche, A. Ageing mechanisms in lithium-ion batteries. *J. Power Sources* **2005**, *147*, 269–281.
21. Eddahech, A. Modelisation du vieillissement et determination de l'etat de sante de batteries lithium-ion pour application vehicule electrique et hybride, Université Sciences et Technologies - Bordeaux, 2013.
22. Schmalstieg, J.; Käbitz, S.; Ecker, M.; Sauer, D. U. A holistic aging model for Li(NiMnCo)O2 based 18650 lithium-ion batteries. *J. Power Sources* **2014**, *257*, 325–334.
23. Delaille, A.; Grolleau, S.; Duclaud, F. SIMCAL Project: calendar aging results obtained on a panel of 6 commercial Li-ion cells. In *Electrochemical Energy Summit de l'Electrochemical Society*; 2013; Vol. 101.
24. Guena, T.; Leblanc, P. How Depth of Discharge Affects the Cycle Life of Lithium-Metal-Polymer Batteries. *INTELEC 06 - Twenty-Eighth Int. Telecommun. Energy Conf.* **2006**, 1–8.
25. Sarasketa-Zabala, E.; Laresgoiti, I.; Alava, I.; Rivas, M.; Villarreal, I.; Blanco, F. Validation of the methodology for lithium-ion batteries lifetime prognosis. In *EVS27 Electric vehicle symposium*; 2013; pp. 1–12.
26. Martinez-Laserna, E.; Sarasketa-Zabala, E.; Stroe, D.; Swierczynski, M.; Warnecke, A.; Timmermans, J. M.; Goutam, S.; Rodriguez, P. Evaluation of Lithium-ion Battery Second Life Performance and Degradation. In *IEEE Energy Conversion Congress and Expo*; Milwakee, 2016.