Techno-economic Analysis of Second Life Electric Vehicle Batteries for Stationary Energy Storage Applications

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Abstract

The increasing adoption of electric vehicles (EVs) has led to large numbers of retired EV batteries, raising significant environmental and economic concerns. This study aims to ease these concerns by exploring the potential second-life applications of EV batteries, particularly for stationary energy storage. We propose a techno-economic model to analyze the feasibility of using second-life batteries (SLBs) for stationary energy storage in community microgrids with renewable energy resources as well as for load frequency control of ancillary services. This model evaluates the economic residual value against the remaining life cycles of the EV batteries across different second-life applications. Our findings suggest that among all the proposed stationary storage applications, using SLBs for load frequency control of ancillary services is the most economically feasible and beneficial second-life application, followed by their use in community microgrids under an optimization-based control method. The proposed techno-economic model offers valuable insights to stakeholders, such as EV manufacturers and drivers, enabling informed decision-making regarding the second-life use of EV batteries.

Keywords: electric vehicle (EV), stationary energy storage, second life battery (SLB), techno-economic mode

1. Introduction

The rapid growth in the adoption of electric vehicles (EVs) worldwide has given rise to an inevitable side-effect: an increasing number of retired EV batteries. These batteries, which may no longer meet the rigorous demands of powering an EV, still possess a considerable amount of unused energy potential. This potential, if harnessed, can be redirected towards stationary energy storage. Such a repurposing solution not only aids in waste management and environmental preservation but also provides a viable solution for storing renewable energy, reducing peak electricity demand, and improving grid stability. Additionally, this second life application can extend the useful life of EV batteries, and further maximize their value beyond their initial automotive use.

An intriguing aspect of the literature on this topic is the evolution of the EV battery storage field. According to research conducted by Source Forecast [1], there has been a tenfold increase in the size of EV battery storage over the last decade, and the price has fallen to a quarter of what it was a decade ago. The inception of this trend dates back to 2011, when companies first began reusing retired EV batteries, resulting in a significant expansion in second-life applications over the past decade [2]. Pioneering projects have been undertaken to harness the potential of these batteries. For example, in 2011, General Motors and ABB powered a GM office building using five Chevrolet Volt Li-Ion batteries (80kWh), 74 kW solar panels, and 2 kW wind turbines [3]. A collaborative initiative between Daimler, GETEC, Mobility House Remondis, and EnBw in 2016 marked another significant milestone, establishing a 13MWh energy storage system using 1000 used batteries from Daimler EVs, which was the largest second-life application worldwide until two years later [4,5]. Further advancement was observed when Daimler and Ener-City reassembled 1800 retired EV batteries to create a grid-connected storage system with a substantial capacity of 17.4 MWh [6,7]. Existing literature reveals that second-life battery (SLB) projects have demonstrated the viability of a standard production procedure involving disassembling, testing, and reassembling [8]. This burgeoning field offers promising avenues for future research and potential solutions to current energy storage challenges. Techno-economic analysis typically encompasses an evaluation of the batteries' technical and economic feasibility, considering factors such as the state of health of the batteries, expected performance and lifetime, cost, reengineering expenses, and economic benefits of usage [9]. Developing strategies based on these evaluations can be crucial to reduce the cost of battery storage systems, a significant barrier to their widespread adoption in renewable energy systems [10].

Despite the compelling advantages of using second-life EV batteries for stationary energy storage, the field is still maturing, and several research gaps persist. Notably, there is a scarcity of techno-economic analysis for the specific use of second-life EV batteries in community microgrids powered by renewable energy sources and for load frequency control in power grids. Also, there is an urgent need for the development of sophisticated control algorithms tailored for these specific applications. Furthermore, comprehensive analyses considering a wider range of factors affecting the economic benefits and technical performance of second-life batteries are noticeably absent.

This paper aims to address these research gaps and contribute to the growing body of knowledge in this field. We propose a novel techno-economic analysis on the feasibility of using second-life batteries for stationary energy storage. Our model investigates the economic residual value versus the battery's remaining life cycles. It considers a variety of factors, including different control algorithms, battery internal resistances, re-engineering costs, and local electricity tariffs. Our research extends beyond presenting a theoretical model by also offering practical insights. These insights can guide the auto industry and relevant stakeholders in creating comprehensive and effective action plans for the second-life use of EV batteries.

2. Circular economy and life cycle of an EV battery

The methodology for this study aims to evaluate the feasibility of utilizing SLBs for stationary energy storage, integrating the concept of a circular economy designed to maximize economic benefits. The approach seeks to enhance the use of battery capacity. We divide the life cycle of an EV battery into four stages:

- Stage 1: The batteries are employed in electric vehicles.
- Stage 2: The batteries are repurposed for stationary storage while still within the EVs. Although the vehicle's mechanical and/or battery conditions may not be conducive for continued mobile use, the batteries remain functional. Consequently, the vehicles can participate in energy trading with the grid, a concept analogous to vehicle-to-grid (V2G) systems. Normally, the original EV on-board battery management system (BMS) is use for this stage [11].
- Stage 3: Battery conditions deteriorate, requiring removing batteries from the EVs for reassembly and use in stationary energy storage. The key distinction between Stages 2 and 3 is the need for battery re-engineering and the role of the EV on-board BMS, which is crucial at Stage 2.

- Stage 4: The batteries are no longer suitable for stationary energy storage and are therefore recycled, giving way to the production of new batteries.

This work focuses on evaluating the feasibility of using second-life batteries for stationary energy storage from Stage 2 to Stage 3 or from Stage 1 to Stage 3 directly. Two specific applications are considered: community microgrids with renewable energy resources, and load frequency control. For the first application, we use two control algorithms: time-based control and optimization-based control. The underlying aim of our methodology is to provide a comprehensive analysis to help stakeholders of EV batteries make informed economic choices.

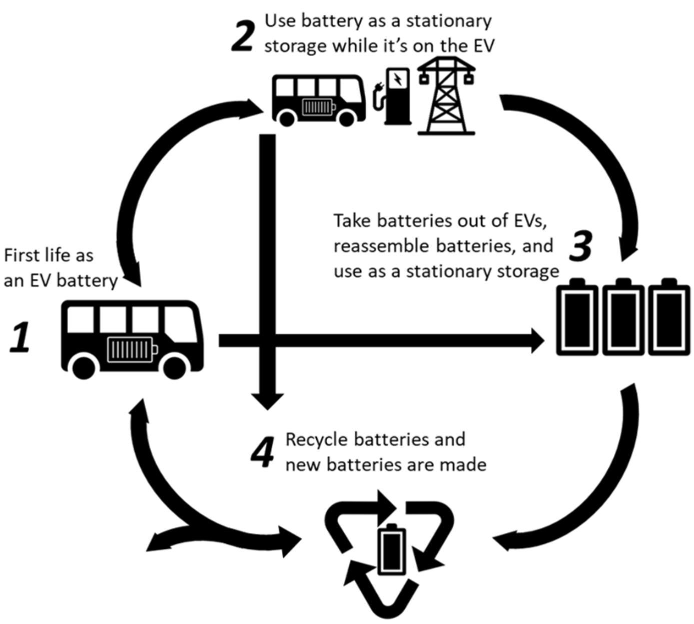

Figure 1 Circular economy for second-life EV batteries

The block diagram of the framework of the techno-economic analysis is shown in Figure 2. The block diagram began with two control strategies for community microgrids integrated with renewable energy sources: a time-based control and an optimisation-based control, while also considering the potential for providing ancillary services like load frequency control. Simultaneously, we examined various impactful factors such as the control method, electricity tariff, internal resistance of SLBs, and their cost. This assessment served as an input to the optimisation process, aimed at maximizing the potential of SLBs in stationary energy storage applications. Subsequently, the economic feasibility of deploying SLBs was evaluated. Depending on the outcome of economic savings, a decision was made: if the savings were positive, the SLBs were reengineered for the new application; if not, they were recommended for recycling. Ultimately, we offered an economic saving projection at different life cycles and suggested appropriate actions based on these findings. This rigorous, multi-level analysis allowed for an in-depth understanding of the various dimensions and implications of using SLBs in stationary energy storage applications.

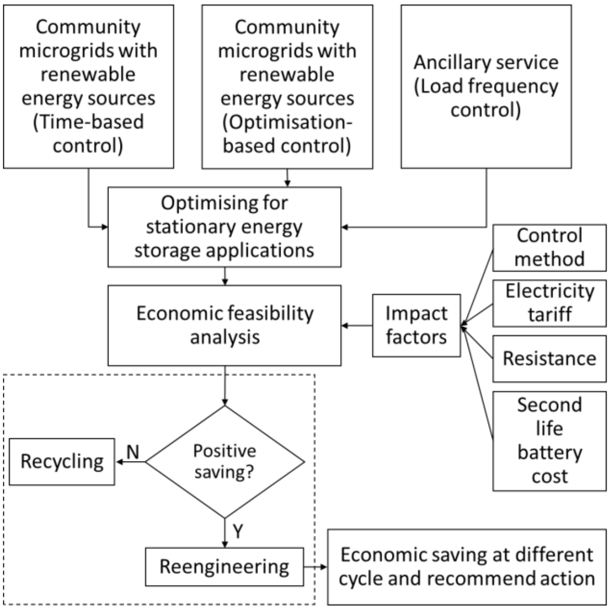

Figure 2 Block-diagram for techno-economic analysis

2.1 Economic model

The economic model is developed considering the energy scenarios of stationary energy storage. Given that battery-involved projects are long-term, we use net present value (NPV) to calculate economic benefit [12]. The decision for making action plans is determined by the net present saving versus the remaining life cycles of second-life batteries. If the NPV result is positive, the batteries are deemed worth reengineering and can generate profit. If the NPV result is negative, the batteries are not considered worth reengineering. The equation for NPV calculation is presented as follows.

$$NPV = \alpha + \sum_{y=o}^{n} \frac{S_{year}(y)}{(1+i)^y} \tag{1}$$

where α is the initial investment and it is normally a negative value. The initial investment includes the cost of battery, logistics and label costs for reengineering the battery. $S_{year}(y)$ is the net saving during a single year y. i represents the discount.

An integral part of our methodology involves the strategic interactions between the different stakeholders involved in the community microgrid. This analysis draws upon the concept of Nash Equilibrium, a key notion in game theory. Named after John Nash, this concept refers to a state of a strategic game in which no player can unilaterally deviate from their current strategy to improve their payoff, given the strategies of the other players. In the context of our study, each stakeholder – battery owners, energy providers, and grid operators – represents a player in this game. Their strategy encompasses decisions on aspects such as the degree of participation in the community microgrid, their use of second-life batteries (SLBs) in stationary energy storage applications, among others. The payoff for each player is the net savings achieved through these decisions. We will compute the Nash Equilibrium of this game under various conditions, which will represent the strategies from which no player will want to deviate unilaterally. Such an analysis will provide us with a deeper understanding of the decision-making processes of the stakeholders and their impact on the overall system performance.

2.1.1 Control algorithms for community microgrids with renewable energy resources

For managing the energy dynamics of community microgrids, two distinct control methodologies are proposed: time-based control and optimization-based control. These methodologies are designed to efficiently control the charging and discharging of second-life batteries in various energy scenarios.

A) Time-based control

Time-based control is a strategy that operates based on real-time electricity prices. It capitalizes on the price differences between peak and off-peak periods, thus creating economic benefits. In this control methodology, batteries are charged during off-peak periods when electricity prices are lower, and discharged during peak periods when electricity prices are higher. This strategy is particularly beneficial in energy scenarios where there is no surplus energy generation (e.g., solar power) or when energy generation is insufficient to meet the energy demand.

Equation 2 shows the energy cost savings for time-based control. The economic benefit can be obtained by the electricity price differences between peak and off-peak time.

$$S_{tot} = \sum_{i=1}^{24} (P_{disc}(i) C_{peak}(i) - P_{char}(i) C_{offpeak}(i)$$

where S_{tot} is the total energy cost saving of whole system, P_{disc} is the discharging power of SLBs, C_{peak} is the electricity price of peak time, P_{char} is the charging power of SLBs, $C_{offpeak}$ is the electricity price of off-peak time.

Equation 3 shows the control algorithm for time-based control, which is charging batteries during off-peak time and discharging batteries during peak time.

$$P_B = \begin{cases} P_{Char}(i) & t = t_{off-peak} \\ P_{Dis}(i) & t = t_{peak} \end{cases} \tag{3}$$

Where P_B is battery power. The battery power became P_{Char}, when the time is off-peak time. The battery power became $P_{Dis}$when the time is peak time.

In this energy scenario, there is no solar generation, or the solar generation is consumed as soon as it is produced. There are no solar power flows into battery. It can be considered as that only three parts which are battery, power grid, and load involved in the process of energy flow. In this case, time-based control was selected. Time-based control is a control methodology that is charging and discharging battery based on electricity price. The electricity price varies based on time. The normal pattern of electricity price is that off-peak price is much lower than peak price. Charging battery during off-peak time and discharging it during peak time. The economic benefit could be gained by the electricity price differences.

B) Optimization-based control

Optimization-based control, on the other hand, leverages linear programming to manage energy generation, demand, battery charging, and discharging with the goal of minimizing the system's operational cost. The control strategy creates an optimized charging and discharging profile for the battery, as well as an importing and exporting profile for the power grid. This methodology becomes relevant in scenarios where there is surplus energy that can be redistributed, i.e., when energy generation exceeds energy demand.

The objective function (4) represents the objective of optimization-based control which is the best benefit that a specific battery energy storage system can get.

$$C_{tot} = min \sum_{i=1}^{24} (C_{imp}(i) E_{imp}(i) + C_{exp}(i) E_{exp}(i)) \tag{4}$$

Where C_{tot} is the total cost of whole system. The economic benefit of the system considers the following: C_{imp} is the cost of energy import from the grid, E_{imp} is the energy import from the grid, $C_{exp}$is the cost of energy export to the grid, E_{exp} is the energy export to the grid, E_{char} is the energy that was charged to the battery, E_{dis} is the energy that was discharged from the battery.

$$\begin{gathered} E_{imp}(i) + E_{solar}(i) + E_{dis}(i) = \\ E_{exp}(i) + E_{load}(i) + E_{char}(i) \end{gathered} \tag{5}$$

The balance equation (5) represents that the system should be always in a dynamic equilibrium. Where E_{solar} is the solar energy generation, E_{load} is the load energy.

$$E_B(i) = E_B(i-1) + E_{char}(i) - E_{dis}(i) \tag{6}$$

The battery energy balance equation (6) represents that the energy discharged from battery should be equal to the energy charged to battery. Where E_B is the energy in the battery.

The following equations (7-10) are the constraints of energy that was charged to the battery, energy that was discharged from the battery, energy import from the grid, and the energy export to the grid.

$$E_{char}^{min} < E_{char} < E_{char}^{max} \tag{7}$$

$$E_{dis}^{min} < E_{dis} < E_{dis}^{max} \tag{8}$$

$$E_{imp}^{min} < E_{imp} < E_{imp}^{max} \tag{9}$$

$$E_{exp}^{min} < E_{exp} < E_{exp}^{max} \tag{10}$$

2.1.2 Load Frequency Control with Second Life Batteries

The equation 11 is the net saving of using SLBs for load frequency control. L is the net saving. SLB stakeholders can be paid by using battery energy storage for load frequency control in the UK is through participation in the National Grid's Balancing Mechanism (BM). Battery energy storage providers can bid to provide frequency response services to the and get paid for their participation, and β is the load frequency control price. η is the battery usage by participating load frequency control.

$$L = \beta\eta \quad (11)$$

3. Case study and Results

In this section, we apply the concept of Nash Equilibrium to analyze the strategies adopted by different stakeholders. Upon analyzing the simulation results, we identified instances where a Nash Equilibrium was reached. In these scenarios, no player could unilaterally deviate from their strategy to improve their net savings, given the strategies of the other stakeholders. This suggests that, under these conditions, the operations of the community microgrid can reach a stable state that is mutually beneficial for all stakeholders.

There are CHP plant generation and PV generation in Cranfield University. The facilities team has provided power profiles at Cranfield University, in particular the annual energy demand, on-site generation data and electricity price.

There is a project that has been working on the reassembling of batteries from one Cranfield electric bus and installing the up-cycled battery at Cranfield DARTeC building. 8 Electric buses with 5-year usage for route 7 at Milton Keynes from 2014 to 2019 and the 8 buses were gifted from eFIS to Cranfield University. 1 electric bus batteries were used as part of the IUK project and total capacity is 100kWh. The energy demand and PV generation for DARTeC building are forecasted based on the profile from facilities team.

50% of energy demand are meet by the electricity that imported from grid. The electricity prices play a crucial role in the cost of energy at Cranfield University. There are 4 parents of price curve. It firstly can be categorized as winter (October to March) and summer (April to September). Then, it can be categorized as weekdays and weekends. There are lots of price differences between peak and off-peak time on both summer and winter weekdays.

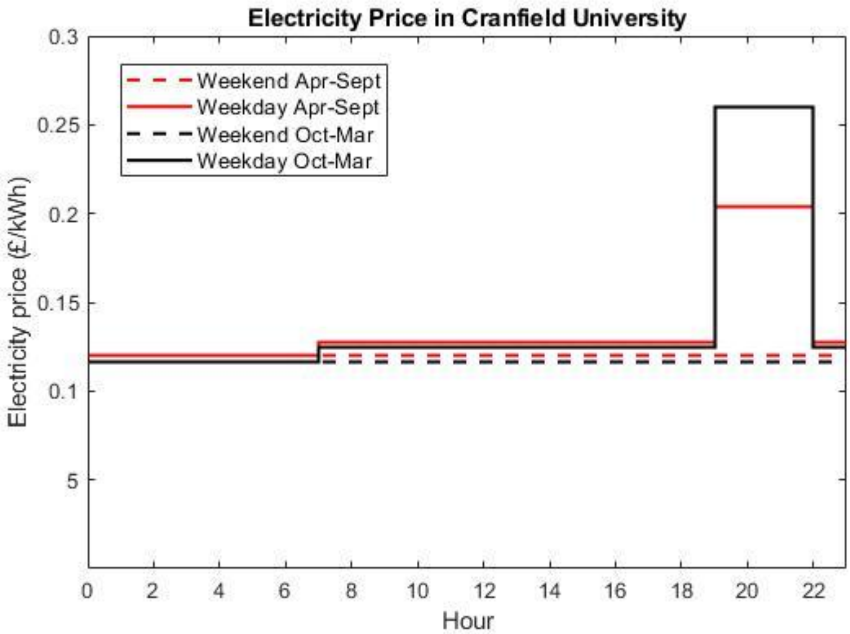

Figure 3 Electricity Price in Cranfield University

3.1 Economic benefits

This chapter is the results comparison between the time-based and optimization-based methods and carbon savings for second life batteries. The total net saving vs remaining life cycles are presented as results.

Every figure has 2 factors, one is SLB cost, and the other one is internal resistance. The reason why there are 3 different SLB cost is that a sensitivity analysis is used to explore how these factors (such as the cost of SLB, reengineering cost, and different internal resistances) affect economic benefit.

Time-based control can generate charging and discharging profile for SLB based on the electricity price curve. Figure 4-6 are the total net saving versus remaining life cycles for time-based control. It is the sensitivity analysis between different SLB costs when the internal resistance is the same.

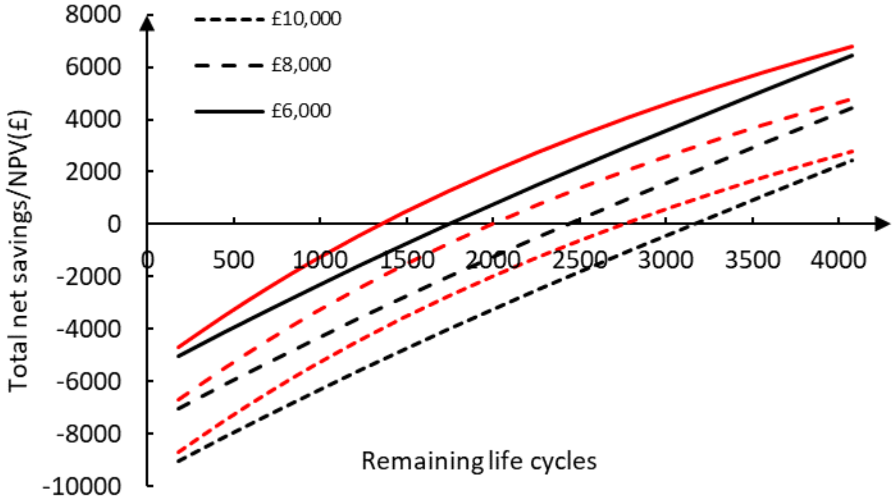

Figure 4 Total net saving vs. remaining life cycles (When the internal resistance is the same at 0.2Ω, the comparison between different SLB costs (£10,000, £8000, £6,000), red lines are the results from optimization-based control, black lines are the results from time-based control)

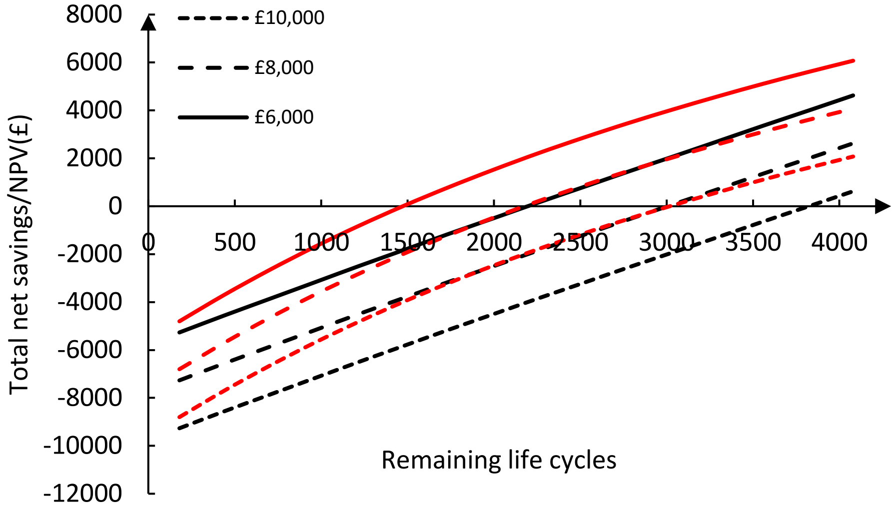

Figure 5 Total net saving vs. remaining life cycles (When the internal resistance is the same at 0.4Ω, the comparison between different SLB costs (£10,000, £8000, £6,000), red lines are the results from optimization-based control, black lines are the results from time-based control)

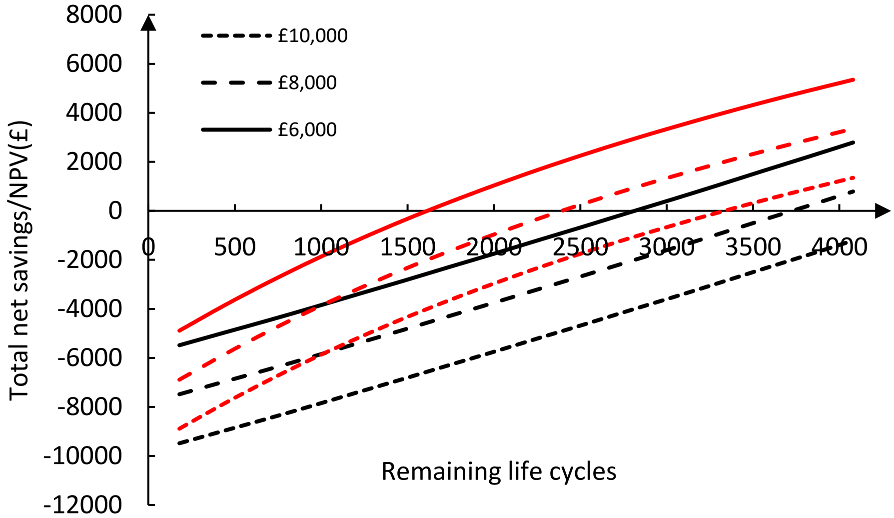

Figure 6 Total net saving vs. remaining life cycles (When the internal resistance is the same at 0.6Ω, the comparison between different SLB costs (£10,000, £8000, £6,000), red lines are the results from optimization-based control, black lines are the results from time-based control)

Optimized control is using linear programming in MATLAB to manage the relations between import energy, charging energy, solar generation, export energy, and discharging energy. The objective function, linear and nonlinear constrains are proposed for this stationary energy storage. Through this optimization, the minimal operation cost can get. Figure 2-4 are the total net saving versus remaining life cycles for optimization-based control. It is the sensitivity analysis between different SLB costs when the internal resistance is the same.

3.2 Residual value versus remaining cycle

The results are presented as economic comparison between the time-based control, optimization-based control and load frequency control for second life batteries. The total residual value versus remaining life cycles is used to show the whole life of second life EV batteries' different life stages. There are 4 curves in total. The first line is EV batteries residual value. The second line is the second life EV batteries residual value while using time-based control. The third line is the second life EV batteries residual value while using optimisation-based control. The last line is the second life EV batteries residual value while providing load frequency control. The line of EV batteries residual value has serval intersections with the rest of lines.

The residual value of EV batteries is on an exponentially decreasing trend. The rate of decline is greatest at the very beginning and then tapers off. The residual value of an EV batteries will always remain positive. The other three lines start out negative and gradually increase, intersecting the residual value curve of the EV batteries to form the first intersection point. This intersection is the point of demarcation between the first and second/third stages of the EV battery lifetimes. This first intersection point means that using EV batteries as stationary energy storage applications has more residual value than using it as just EV batteries, in other words after this intersection point, using the EV batteries as a stationary energy storage application creates more value for the stakeholders.

Based on the methodology, battery cycle daily coemption in all applications is 1. As the battery is used, the last three lines increase and reach a maximum, then the residual value of the second life EV batteries decreases and finally forms a second intersection point with the residual value curve of the EV batteries. This intersection point is the starting point of the fourth stage of the batteries' life. When the EV batteries reach this stage, the tram does not create any more value for the stakeholders and the battery needs to be recycled. Based on the results, the first and second intersection points of time-based control are in the range of day 3018 to day 4700, optimisation-based control are in the range of day 2636 to day 4750, load frequency control are in the range of day 2500 to day 4790. Load frequency control has the longest interval, which means that load frequency control is more feasible and creates more value, followed by Optimisation-based control and finally time-based control. However, all three of these second life applications provide positive economic benefits for EV batteries.

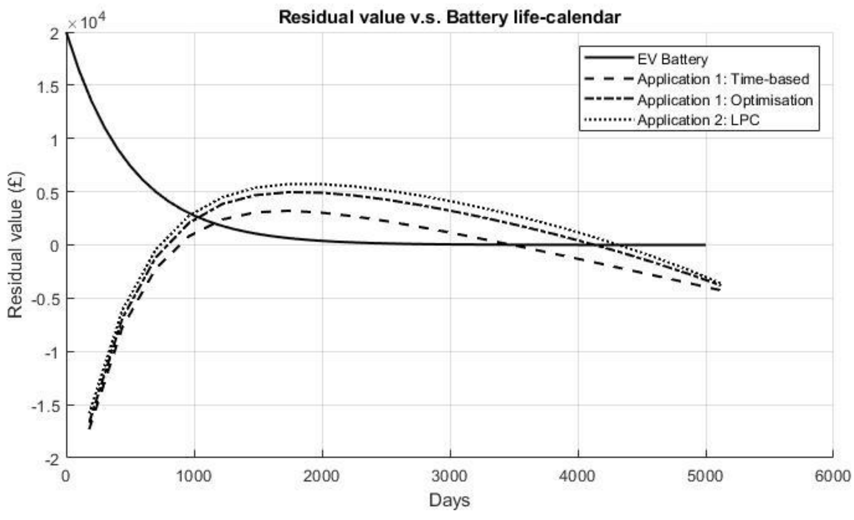

Figure 7 Residual value versus battery life-calendar

4. Conclusions

This study provides a comprehensive investigation into the feasibility of repurposing second-life batteries from electric vehicles for stationary energy storage. The focus of this research is: community microgrids powered by renewable energy resources and load frequency control in power grids. Our research brings to light the significant economic benefits that can be achieved through the economy model for second-life batteries. The investigation commenced with the construction of the economic model that incorporated various factors, including the cost of second-life batteries, battery internal resistance, reengineering costs, local electricity tariffs, and remaining life cycles. By incorporating these factors, our model provided a nuanced understanding of the economic feasibility of repurposing second-life batteries for stationary energy storage.

Our analysis further revealed that the economic benefits of using second-life batteries for stationary energy storage are significant and are influenced by several key factors. Among these are the control algorithm employed and the remaining life cycles of the batteries. The study used two control methods for community microgrids with renewable energy resources: time-based control and optimization-based control, that presented different economic advantages. The choice of the control method was found to be crucial in maximizing the economic benefits of the second-life batteries. The time-based control method capitalizes on real-time electricity prices to regulate battery charging and discharging, whereas the optimization-based control employs linear programming to maximize energy cost savings.

We observed that a Nash Equilibrium was attained under certain conditions, which signifies a stable and mutually beneficial state of operations for all stakeholders. This implies that under such conditions, there might not be a need for external regulatory interventions. However, in scenarios where a Nash Equilibrium was not reached, there might be a requirement for cooperation agreements among the stakeholders or regulatory interventions to achieve an optimal and stable state of operations.

Another important revelation from this research is the correlation between the total net savings and the remaining life cycles of the SLBs. The findings illustrated that as the remaining life cycles of the batteries decrease, so does the economic feasibility of repurposing them for stationary energy storage. This understanding is critical in informing the optimal moment to transition the batteries from one stage to another, thus maximizing their economic value.

In summary, our study sheds valuable light on the potential of second-life batteries in driving economic benefits in the context of stationary energy storage. Our findings underscore the importance of adopting a holistic and nuanced approach in assessing the feasibility of second-life batteries, considering a range of technical and economic factors. This research, therefore, contributes significantly to the burgeoning field of second-life battery studies and offers practical insights for stakeholders seeking to unlock the untapped potential of these resources.

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