The Impact of Different Control Strategies on Residential Battery Degradation

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Introduction

Residential batteries are attracting consumers due to their ability in reducing the electricity bill by maximizing the solar PV self-consumption as well as optimizing the time of use tariff (ToUT). Furthermore, the deployment of residential batteries is increasing due to their potential in supporting the network from the operator's point of view. The control of residential batteries can be categorized into real-time and look-ahead. The real-time control usually aims to achieve self-consumption maximization (SCM) by charging the battery using the excess PV generation. The SCM can be adjusted to optimize the ToUT by charging during low ToUT periods when the PV generation is insufficient. The look-ahead control utilizes the forecasting to schedule the battery using an optimization solver. This work investigates the impact of these three different control strategies on battery degradation for different capacities. Other comparisons for the electricity bill reduction and network losses are also considered.

Methodology

Three residential control methods are used: 1) conventional SCM control, 2) SCM control in addition to ToUT optimization, and 3) day-ahead scheduling with perfect foresight to minimize the electricity bill using WORHP optimizer [1]. The battery model, SCM control method, and the day-ahead optimization are adopted from [2], the second strategy is modified to consider the ToUT optimization by charging the battery during low ToUT periods with a fixed percentage per season that represents the average drop in PV production in each season w.r.t the summer. For each control method, simulation is conducted for one-year and the battery state of charge (SoC) results are fed into a rainflow counting algorithm (RCA). Afterwards, the results obtained from the RCA are fed into Li-ion semi-empirical cycling degradation model [3] to quantify the battery state of health (SoH) at the end of a one-year operation for different control strategies. The proposed methodology framework is illustrated in Fig. 1, and examples of each method for a single day are shown in Fig. 2 – Fig. 4.

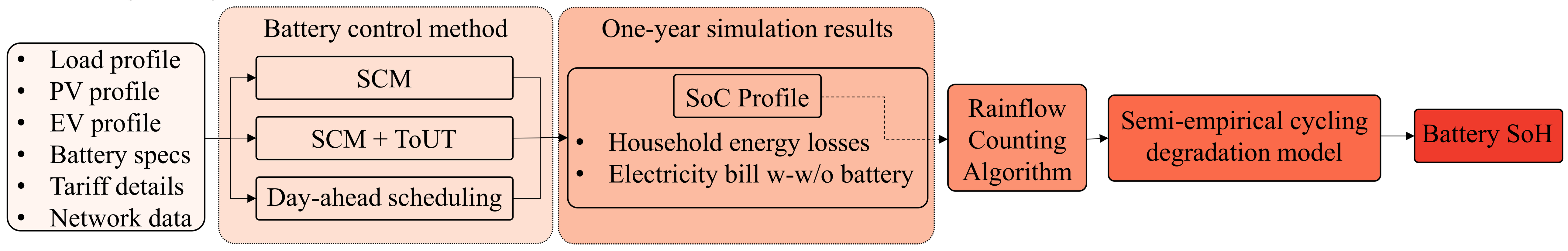

Fig. 1. Proposed methodology framework

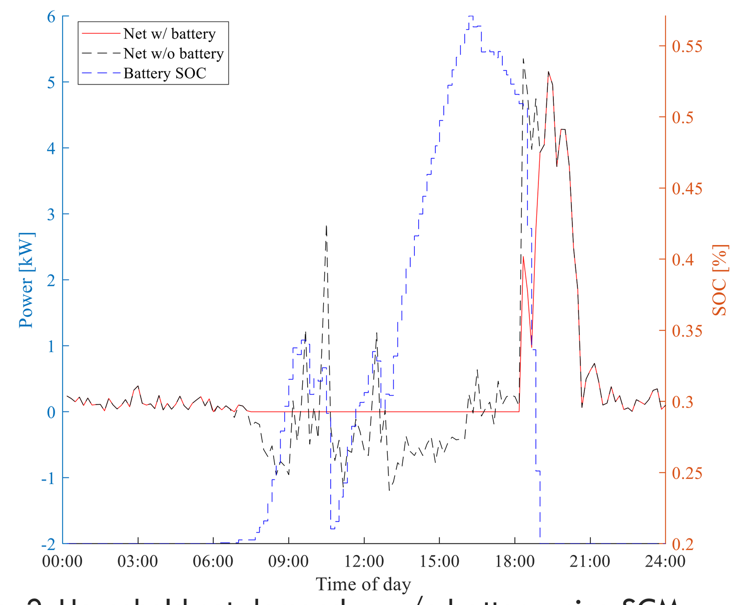

Fig. 2. Household net demand w-w/o battery using SCM

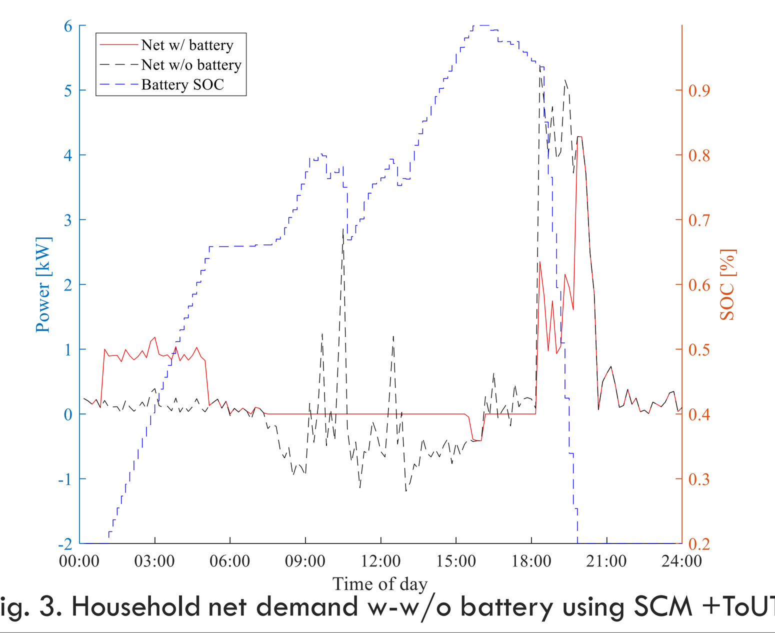

Fig. 3. Household net demand w-w/o battery using SCM +ToUT

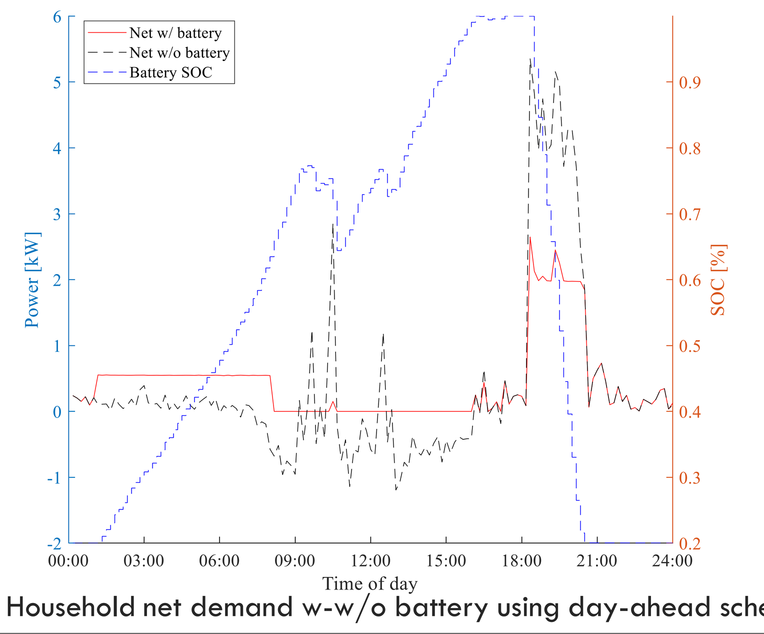

Fig. 4. Household net demand w-w/o battery using day-ahead scheduling

Results

One-year half-hourly measurements were used for a typical household in London with an average daily consumption of 11 kWh/day equipped with a 3.3 kWp PV, and electric vehicle charging profile for the 3 kW standard charger. Five Li-ion batteries represent actual batteries in the market are considered with depth of discharge (DoD) of 80% and round-trip efficiency of 90%.

The results show that there is a significant relationship between battery capacity and degradation. Small batteries tend to degrade faster due to the undergoing complete cycles that small batteries undertake w.r.t to large capacities as shown in Fig. 5. According to Fig. 5, the SCM control method has a lower impact on battery degradation. Combining the ToUT optimization with SCM has shown to accelerate the degradation. While the day-ahead scheduling has the worst impact on degradation. This because day-ahead scheduling utilizes the battery completely to reduce the electricity bill, especially with a robust forecast. Most of the residential batteries have a lifetime of 10 years, however, the actual battery lifetime can be affected by the control method. For instance, the battery reaches its end of a lifetime when its SoH reaches 60% - 80% [3], with the day-ahead scheduling, smaller batteries may have to be replaced before the end of 10 years as the SoH after 10 years for the 2.4 kWh is 49.6% and 56.7% for the 4.8 kWh battery as shown in Fig. 6. Yet, the day-ahead scheduling has a better impact on the electricity bill and loss reductions (11.5% and 57% increase on average in electricity bill and loss reductions respectively compared to the other two methods) as shown in Fig. 7 and Fig. 8. Optimizing the ToUT with SCM has been shown to have a moderate impact on the degradation where the SoH after 10 years operation of the 2.4 kWh and 4.8 kWh batteries are 58.7% and 68.6% respectively. On average, the electricity bill can be reduced further by 10%, and the loss reduction can be improved by 10.2% compared to the SCM only.

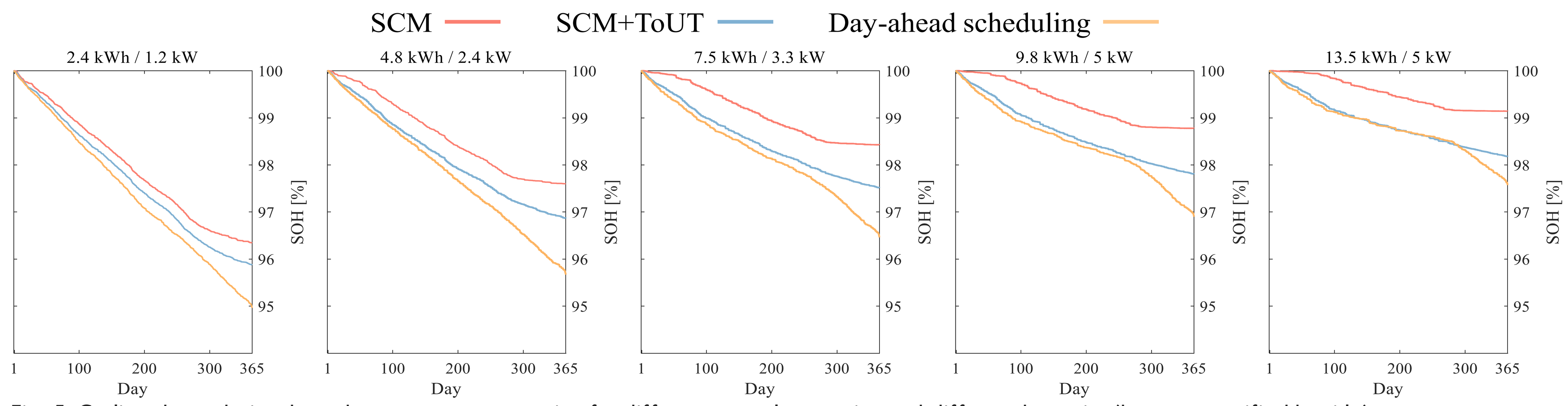

Fig. 5. Cycling degradation throughout one-year operation for different control strategies and different batteries (battery specified by title)

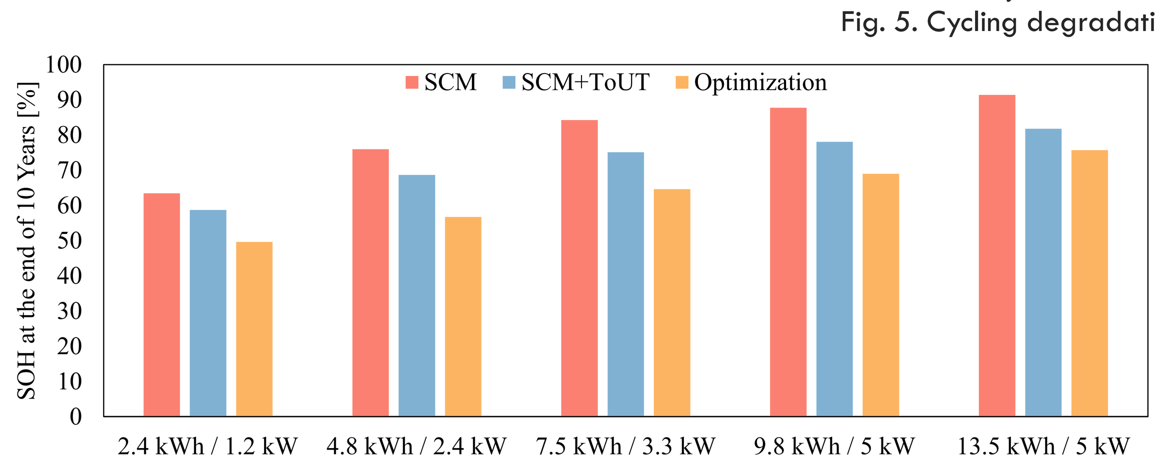

Fig. 6. Battery SOH at the end of 10 years operation

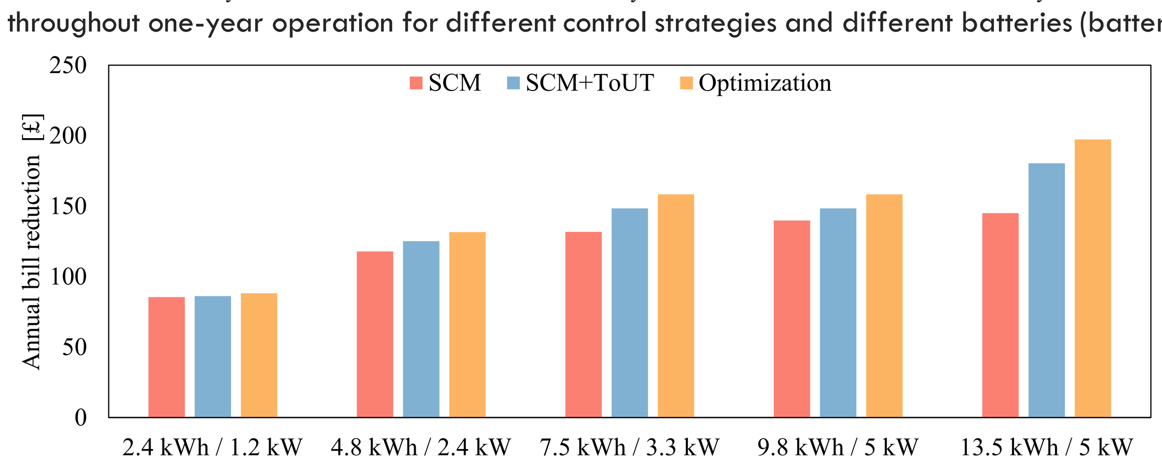

Fig. 7. Annual reduction in electricity bill

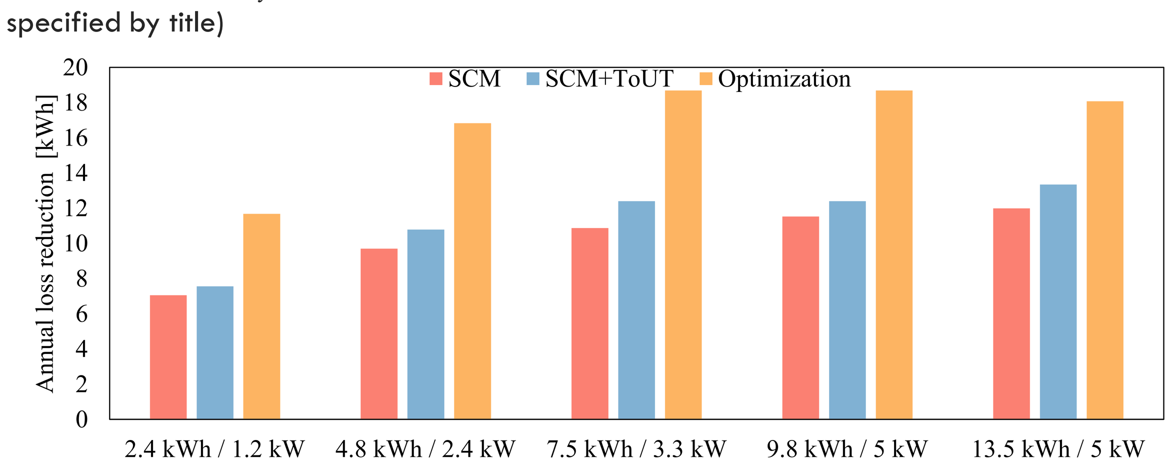

Fig. 8. Annual reduction in energy loss

Conclusions

This work shows that the residential battery should be controlled properly to prolong the battery lifespan. Adopting SCM will preserve the battery capacity for longer periods compared to other methods. However, it has a lower impact on losses and bill reductions. Operating the battery using SCM+ToUT or day-ahead scheduling will have a better impact on the losses and bill reductions. However, the battery capacity fades faster. Hence, the battery owner should set the priorities in determining the control method. Furthermore, battery capacity plays an important role in battery degradation. Small batteries should be operated for SCM only to maintain reliability throughout the 10 years lifetime stated by the manufacturers. While large batteries proved the efficacy to maintain the battery SOH under all the control methods. It should be noted that in the previous methodology, cycling ageing was only considered. Yet, the battery capacity fades also due to calendric ageing which depends on the DoD, cell temperature and cycling behaviour and can increase the loss in battery capacity by 1% per annum on average. For future work, the impact of DoD and E-rate on battery degradation under different control methods will be investigated.

References

[1] C. Büskens and D. Wassel, 'The esa nlp solver worhp', in Modeling and optimization in space engineering, Springer, 2012, pp. 85–110.
[2] A. A. R. Mohamed, R. J. Best, X. Liu, and D. J. Morrow, 'Domestic Battery Power Management Strategies to Maximize the Profitability and Support the Network', IEEE PES General Meeting, 2021, pp. 1–5, to be published.
[3] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, 'Modeling of lithium-ion battery degradation for cell life assessment', IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 1131–1140, 2016.

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