

Techno-Economic Impact of Li-ion Battery Lifetime Modelling on Energy Storage System Sizing

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Abstract

The present work aims at evaluating the impact of battery ageing model accuracy on the optimal energy storage system (ESS) sizing. A hybrid ESS is optimized for a tramway application, considering two different ageing models: a Whöler curve based ageing model and a semi-empirical model. Results show significant savings of *c.a.* 8% over energy operating costs when the ESS sizing is performed with an accurate battery ageing model.

Keywords: Battery, Energy Storage, Battery Model, Optimization, Cost.

1 Introduction

In the last years the electrification of the transport sector has become one of the main research focuses for Original Equipment Manufacturers (OEMs), industry, research centres and academia. However, high costs and limited lifespan of most energy storage technologies remain hampering massive adoption of alternative electromobility solutions. This is the case of onboard battery-based ESS, which is widely considered as the main solution to drive the change towards zero emission vehicles. Thereby, the proper sizing of ESS, as well as the applied energy management strategy strongly impact the ESS lifespan, and thus, the techno-economic viability of on-board ESS solutions.

Most publications rarely emphasise on lifetime modelling when describing the sizing of battery ESS solutions. Some authors do not even consider battery degradation, while others consider semi-empirical ageing models or high-complexity electrochemical models [1]. Nevertheless, the most widespread approach is to rely on Whöler curve based ageing models for sizing purposes [2], [3], due to low computational cost and the required low experimental work (some manufacturers even provide such Whöler curves with their batteries).

There is not a clear conclusion about how the error on battery lifetime estimation affects the final battery pack sizing for a certain application, and what economical implication such ‘non-optimal sizing’ entails. The present work evaluates these issues, by comparing the sizing optimization results obtained from two different approaches: a Whöler curve based ageing model and a semi-empirical ageing model.

2 Scenario Overview

A tramway system application has been considered as case study to perform the comparison between the sizing results obtained with the two considered ageing models. Including an on-board ESS in a tramway can contribute to the following improvements:

- Power peak shaving demanded during acceleration, which leads to reduced power requested to the supply line (catenary).
- Limitation of voltage drops in the main grid, which might allow a higher traffic density without further modification in the existing infrastructure.

- Certain driving autonomy for emergency situations (unscheduled stops), or in catenary-free zones.

A hybrid ESS that consists of supercapacitors (herein referred as SC) and lithium-ion batteries (herein referred as BT) has been considered as an optimal solution for the tramway application. During operation, SC absorb or inject power peaks during regenerative braking and acceleration events, respectively. On the other hand, BT are used as auxiliary energy source in areas with catenary, and as primary energy source in catenary-free zones.

Among the different possible hybrid ESS connection topologies [4], a fully active or parallel connection topology was selected to allow decoupling the use of BT and SC, maximizing the functionalities of each energy storage technology. Figure 1 depicts the parallel connection topology implemented.

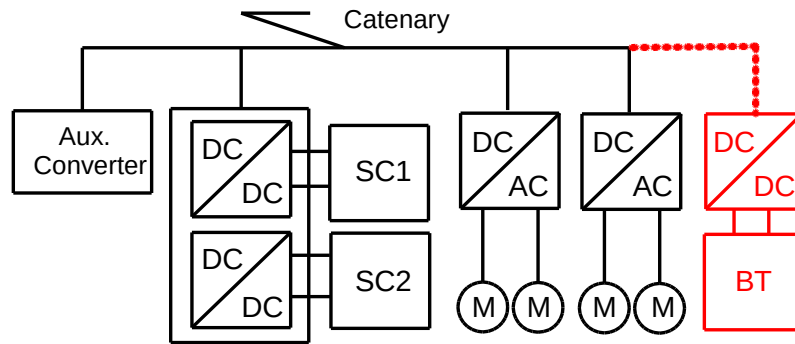


Figure 1: Hybrid ESS connection topology to the tramway powertrain

The scenario of this paper considers the energy and power requirements of a particular case study: a city route of the tramway with several stops and a pedestrian section with a catenary-less zone of 500 m, speed limit of 15 km/h (in the catenary-less zone) and maximum slope of 0.6%. Figure 2 shows the considered train speed and power profile, which corresponds to the city route section (single round-trip travel) described previously. The shadowed sections represent the catenary-less zones.

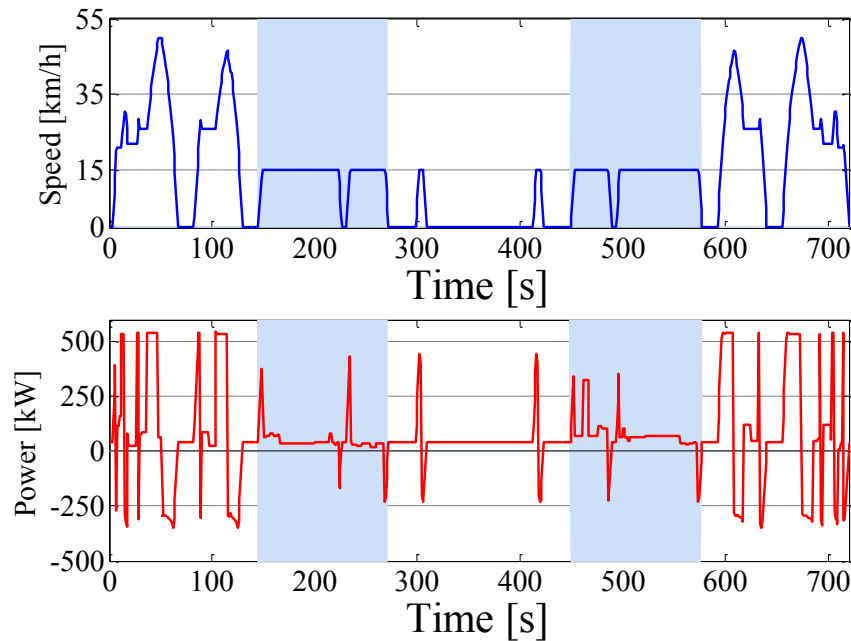


Figure 2: Tramway route and power demand for the route scenario considered onboard ESS ageing modelling

3 Onboard ESS ageing modelling

The hybrid ESS considered in this application is composed of both SC packs and Li-ion BT packs connected on a parallel topology, as described in the previous section. For the electrical modelling of the two different energy storage technologies, the approach from V. Herrera *et al.* [5] was followed to keep the analysis simple and the computational effort low, as the present work is mainly focused on the evaluation of the Li-ion battery ageing model impact over the optimal sizing result.

A supercapacitor model consisting of a capacitor C_{SCcell} [F] in series with a resistance $R_{int-SCcell}$ [Ω] has been simply implemented. Assuming that a string contains n_{SC} supercapacitor cells in series and the SC pack groups m_{SC} strings in parallel, the equations describing the electrical behaviour of each SC pack were implemented as follows:

$$C_{SC} = m_{SC} \cdot C_{SCcell} / n_{SC} \quad (1)$$

$$R_{SC} = n_{SC} \cdot R_{int-SCcell} / m_{SC} \quad (2)$$

Being C_{SC} and R_{SC} the total capacity [F] and the equivalent internal resistance [Ω] of the SC pack.

Regarding the Li-ion BT, a 2.3 Ah LFP-based Li-ion battery cell is considered in the present study. Similarly to the case of the SC pack, each Li-ion battery has been modelled by means of the open circuit voltage (OCV) of the cell in series with a resistor, which models the DC internal resistance of the cell. Assuming that a string contains n_{BT} battery cells in series and the BT pack groups m_{BT} strings in parallel, the equations describing the electrical behaviour of each BT pack are implemented as follows:

$$V_{BT} = V_{OCV-BTcell} \cdot n_{BT} \quad (3)$$

$$R_{BT} = n_{BT} \cdot R_{int-BTcell} / m_{BT} \quad (4)$$

Being V_{BT} and R_{BT} the total voltage [V] and the equivalent internal resistance [Ω] of the BT pack.

Regarding the ageing behaviour of the hybrid ESS, a different approach has been followed for modelling the SC and BT packs. Considering that the number of cycles that SC can perform is significantly large compared to the BT, and taking into account that the calendar aging of SC is almost negligible when stored at proper conditions, a constant value of 10^6 cycles has been implemented as the upper limit for SC lifetime. As for BT lifetime, two different ageing models were considered to evaluate BT ageing model impact on ESS sizing: i) a Whöler curve based ageing model and ii) a semi-empirical ageing model. These two different approaches represent different levels of complexity and experimental labour costs, but also are unequally accurate for prediction BT lifetime on real operation condition. Both ageing models are described in detail in the following subsections.

3.1 Whöler curve based ageing model:

The use of Whöler curve based ageing models is typically considered in literature, especially for sizing purposes or for economic viability calculation in applications where a battery ESS is integrated.

The idea behind this modelling approach consists of mathematically expressing the number of events i that can occur during the lifetime of a battery until it reaches its EOL, as indicated in Eq. (5). In this case, i represents a certain Depth of Discharge (DOD) and the model evaluates the effect of the DOD upon the degradation of the battery using a *Rainflow cycle counting algorithm*. LL_i represents the lifetime decrease caused by the occurrence of a certain number of i events (*i.e.* the number of charge-discharge full cycles at a certain DOD).

$$LL_i = \frac{NE_i}{NE_i^{max}} \quad (5)$$

where NE_i^{max} is the maximum number of events i that the battery can withstand and NE_i the number of events accounted.

Thereby, LL_i represents the lifetime lost as consequence of the occurrence of a certain number of i events – i.e. the number of charge-discharge full cycles at a certain DOD –. Similarly, for the whole range of DOD (from 0 to 100%), the total loss of lifetime is expressed according to equation (6):

$$LL = \sum_i LL_i \quad (6)$$

Accordingly, when the lifetime lost LL equals 1, it is considered that the cell has reached the end of life (EOL).

This method allows evaluating the corresponding loss of lifetime for a certain battery State of Charge (SOC) profile, from which the number of events at each DOD range can be defined. Then, considering the duration of SOC profile introduced, the total lifetime can be calculated as the inversion of LL , typically defined in years (for a one-year SOC profile):

$$Lifetime = \frac{1}{LL} \quad (7)$$

The maximum number of events NE_i^{max} at each DOD that the cell can withstand is deduced from the Whöler curve of the batteries considered. In this case, for the LFP cell considered, a Whöler curve obtained from experimental testing has been used, as shown in Figure 3 [6].

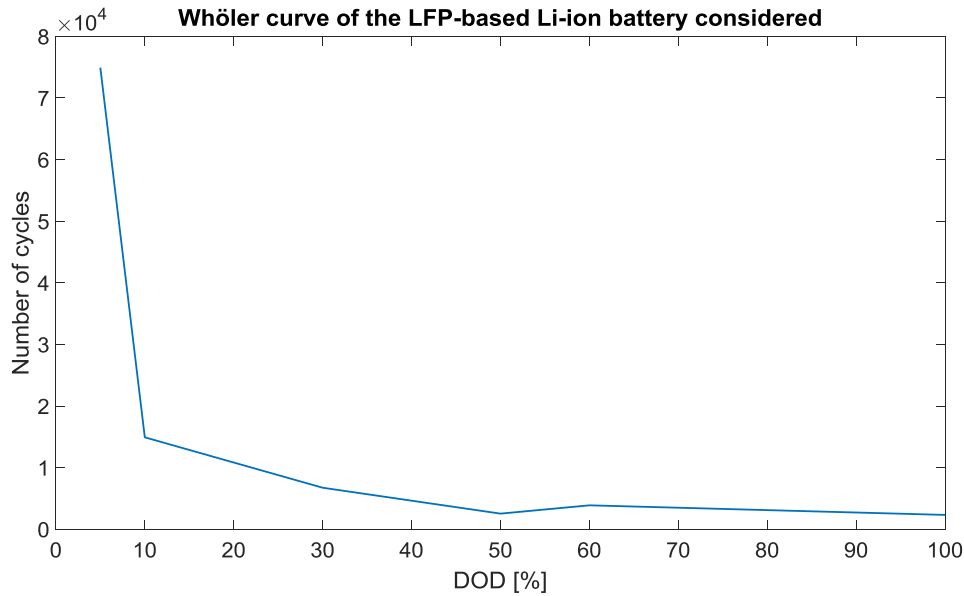


Figure 3: Number of cycles versus DOD curve considered for the Whöler curve based ageing model of the BT [6].

3.2 Semi-empirical ageing model:

A thorough semi-empirical lifetime model comprising both cycling and calendar ageing was also considering in the study. Such ageing model allows evaluating more accurately the ageing model effects over ESS sizing results when considering complex models with very low prediction errors [6]. The Empirical model here presented evaluates the capacity fade over time by superimposing the effect of calendar and cycle operation.

The calendar life model [7] calculates the capacity loss, $Q_{loss_{cal}}$ [%], according to equation (8):

$$Q_{loss_{cal}} [\%] = \alpha_1 \cdot e^{\beta_1 \cdot T^{-1}} \cdot \alpha_2 \cdot e^{\beta_2 \cdot SOC} \cdot t^{0.5} \quad (8)$$

where T [°C] and SOC [%] are the ambient temperature and the state of charge at which the cell is stored, t is time elapsed on storage and $\alpha_1, \alpha_2, \beta_1, \beta_2$ are fitting coefficients.

The cycle life model considered [8] calculates the capacity loss, $Q_{loss_{cyc}}$ [%], according to equations (9,10). In this case, the effect of the C-rate was neglected (when operating under the current conditions specified by the manufacturer) and only the effects of the DOD and the Ampere hour throughput have been considered. Details about cycle ageing behaviour and specific modelling issues can be found in Refs. [8], [9].

$$Q_{loss_{cyc}}[\%](10\% \leq DOD \leq 50\%) = (\gamma_1 \cdot DOD^2 + \gamma_2 \cdot DOD + \gamma_3) \cdot k \cdot Ah^{0.87} \quad (9)$$

$$Q_{loss_{cyc}}[\%](10\% > DOD > 50\%) = (\alpha_3 \cdot e^{\beta_3 \cdot DOD} \cdot \alpha_4 \cdot e^{\beta_4 \cdot DOD}) \cdot k \cdot Ah^{0.65} \quad (10)$$

where $Q_{loss_{cyc}}$ is the equivalent capacity fade caused by cycling [%], DOD [%] represents the DOD at which the cycles are being performed and the Ah the Ampere hours-throughput during the considered cycling period. Additionally, $\gamma_1, \gamma_2, \gamma_3, \alpha_3, \alpha_4, \beta_3$ and β_4 are constant fitting coefficients and k represents the acceleration factor of the cycling ageing tests [8].

Finally, the resultant total capacity loss Q_{loss} [%] is calculated as the superposition of the capacity loss caused by calendar life $Q_{loss_{cal}}$ and by cycle life ageing $Q_{loss_{cyc}}$ [9] as shown in equation (11).

$$Q_{loss}[\%] = Q_{loss_{cal}} + Q_{loss_{cyc}} \quad (11)$$

The precision of this model has been thoroughly validated under different ageing conditions based on the methodology deeply described in [6], [9]. For all the cases considered in validation, the RMSE prediction error calculated for the semi-empirical ageing model was below 1.4%.

4 Energy Management Strategy and Optimization Problem formulation

4.1 Rule Based Energy Management Strategy

A Rule Based Strategy (RBS) has been developed to manage the energy flows in the tramway system. The RBS considers different operating modes, for a tramway running in zones with and without catenary, and operating with two different storage system technologies working simultaneously (BT and SC), as shown in Figure 4:

- Charging mode (CM): When the tramway is stopped at a station (before entering a catenary-less zone) SC are charged using a power control strategy. The BT is not charged at this stage.
- Catenary support mode (CSM): While the tramway is running in a catenary zone, the ESS plays a double role: i) power supply for traction (provided by the BT) with power peak regulation during acceleration (provided by the SC), and ii) braking energy recovery (provided by the BT) with power peak regulation during regenerative braking (provided by the SC).
- Autonomous mode (AM): While the tramway operates in a catenary-less zone, the ESS must fulfil the energy and power demanded.

The RBS adopted as energy management strategy defines the power targets for the BT pack (P_{BT}) and SC pack (P_{SC}) as well as the power requested to the catenary (P_{CAT}) during the tramway operation depending on: the zone where the vehicle is running (operating modes), and the power demand (P_{DEM}) for traction ($P_{DEM} \geq 0$) or regenerative braking ($P_{DEM} < 0$). It is worth mentioning that in CSM, the energy management strategy provides power targets for the BT and SC pack operation. During traction ($P_{DEM} \geq 0$) the catenary injects the remaining power that has not been supplied by the hybrid ESS to fully supply the

tramway demand. On the contrary, in the regenerative braking phase ($P_{DEM} < 0$), the remaining power that has not been absorbed by the hybrid ESS is dissipated as heat in the crowbar resistance (P_{CB}). In AM, the EMS only provides the power target for the BT pack operation in traction and regenerative. During traction ($P_{DEM} \geq 0$) the SC pack injects the remaining power to fully supply the tramway demand. On the other hand, the SC pack absorbs the remaining power during regenerative phase ($P_{DEM} < 0$). In case of power surplus during the regenerative phase, it is absorbed in the crowbar resistance.

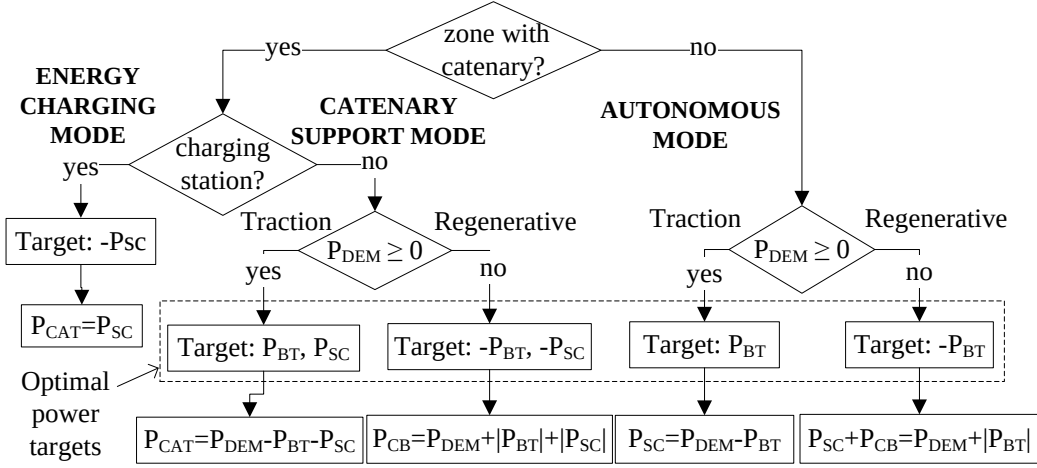


Figure 4: Flow diagram of the RBS implemented

The optimal power targets displayed in Figure 4 are also optimized by the optimization algorithm presented in the following subsection (Section 4.2).

4.2 Optimization problem formulation

Taking into account that the power split ratio among the energy sources (BT, SC and catenary) results in a competitive problem, a multi-objective optimization is proposed:

$$\min_{X \in \Omega} C_T(X) = [BT_{Tcost}(X), SC_{Tcost}(X), GRID_{Tcost}(X)] \quad (12)$$

The fitness function applies an economic model to find the set of optimal solutions that minimize the BT cost (BT_{Tcost}), SC cost (SC_{Tcost}) and grid cost ($GRID_{Tcost}$). For the first two, the economic model considers the initial investment cost and replacement cost (determined by the ageing model considered). This way, the BT costs BT_{Tcost} [€/day], are decomposed in the following cost components:

$$BT_{Tcost} = (BT_{M,y} + BT_{Ca,y} + BT_{Re,y})/360 \quad (13)$$

being $BT_{M,y}$ [€/year] an average value related to the maintenance cost of the BT pack, $BT_{Ca,y}$ [€/year] the annualized capital cost related to the initial investment for the BT pack and $BT_{Re,y}$ [€/year] the annual battery replacement costs. $BT_{Ca,y}$ [€/year] is calculated as follows:

$$BT_{Ca,y} = (C_{kW_{PC}} \cdot P_{PC_{BT}} + C_{kWh_{BT}} \cdot Ca_{BT}) \cdot CRF \quad (14)$$

being $C_{kW_{PC}}$ [€/kW] the referential cost of the power converter associated to the battery pack and $P_{PC_{BT}}$ is the power rating of such converter [kW]; $C_{kWh_{BT}}$ is the referential cost of the of the battery technology [€/kWh] and Ca_{BT} is the installed capacity of the BT [kWh] obtained from the optimization process. CRF [1/year] is the capital recovery factor, which allows annualizing the cost components taking into account the lifespan considered for the whole system [10], and is calculated as follows:

$$CRF = \frac{I \cdot (1 + I)^T}{(1 + I)^T + 1} \quad (15)$$

where I and T are the interest rate and the lifetime of the whole system (tramway) in years, respectively. Similarly, BT_{Rey} [€/year] are described according to equation (16):

$$BT_{Rey} = \sum_{k=1}^n (1 + I)^{-k \cdot Life_{BT}} \cdot C_{kWh_{BT}} \cdot Ca_{BT} \cdot CRF \quad (16)$$

being n the number of BT pack replacement during the lifetime of the system T , and $Life_{BT}$ the lifetime of the battery pack, calculated according to any of the ageing models previously described in section 0.

For the SC case, all the costs components are calculated in an analogous way, but considering in this case the characteristics of the SC pack and the boundary of 10^6 cycle lifetime. Finally, grid costs, $GRID_{Tcost}$ [€/day], i.e. cost associated to the energy absorbed from the catenary, are calculated according to equation (17):

$$GRID_{Tcost} = \sum_{i=1}^N (P_{CAT}(i) \cdot C_{kWh_g} / 3600) \text{ [€/day]} \quad (17)$$

where N is the number of discrete states in the route profile (time step of 1s), $P_{CAT}(i)$ is the power absorbed from the catenary at each discrete state i , and C_{kWh_g} is the referential cost of energy from grid in [€/kWh].

Taking into account the presented cost calculation framework, a multi-objective optimization is carried out by means of Genetic Algorithms (GA). The flow diagram considered is shown in Figure 5. For each individual a particular ESS size is established as well as the power targets for the RBS. The application profile is analysed by simulating the power demanded by the tramway to perform the defined route. The RBS determines the daily power demanded to the BT, SC, and the grid. If the energy management algorithm determines that the considered sizing is not able of fulfilling the power demanded by the tramway to cover route considered, the solution is automatically discarded. Otherwise, two different paths are considered depending on the BT ageing model selected:

- If the considered ageing model is the Whöler curve based ageing model, direct battery lifetime estimation is performed according to the model described in Section 3.1. Then the cost functions are calculated for each individual.
- On the contrary, if the considered ageing model is the Empirical ageing model, an iterative process is followed (marked as a red path in Figure 5) until BT current capacity reaches a defined EOL. This way, battery performance is re-evaluated after every three months of operation (for which the daily operation profile is extended), taking battery degradation into account. Finally, costs are evaluated to finish with the analysis of the individual considered.

After evaluating all the individuals in a generation, the GA modifies the population for the next generation via crossover or mutation operators. There is no global optimal solution for all the three components objective function in equation (12). In each generation, the population “evolves” toward a set of alternative optimal solutions until the stop criteria is reached (in this case the number of generations).

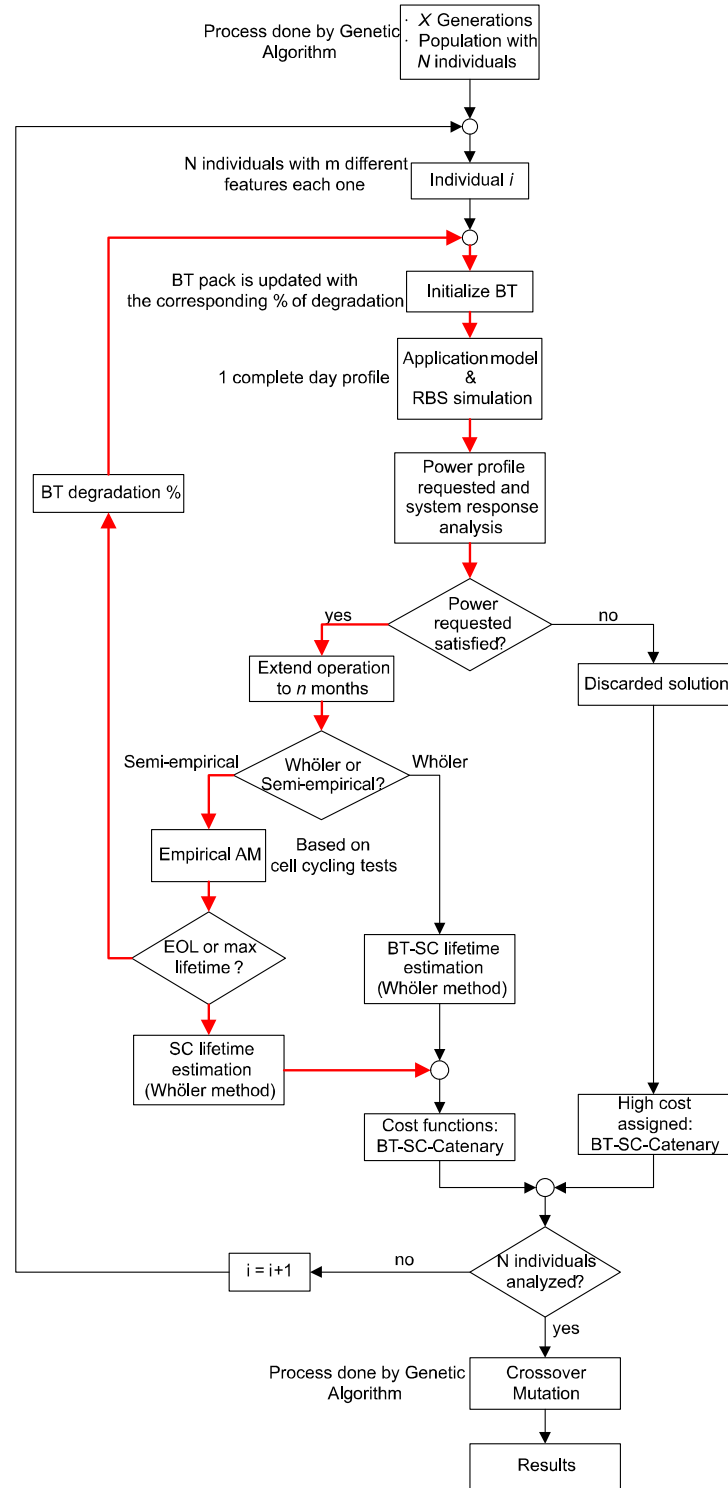


Figure 5: Flow diagram of the GA based optimisation problem.

5 Results and discussion

Two different optimization simulations were run each with one of the ageing models described in Section 3. Both simulations considered the same initial parameters in terms of the tramway route, cost inputs, and system boundaries. Figure 6 presents the optimal set of results calculated for each of the ageing models considered and the overall optimal solution is highlighted with a data tip.

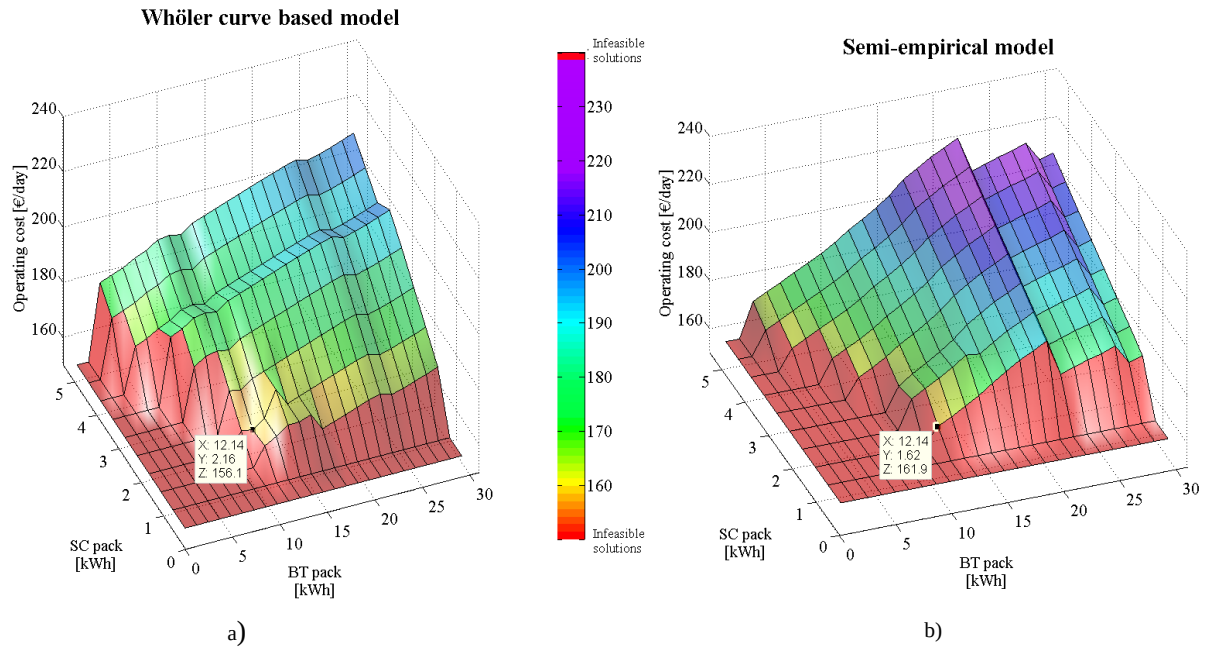


Figure 6: Comparison of the optimal set of results obtained a) Whöler curve based model and b) Semi-empirical model

As it can be observed in Figure 6, results obtained using the Whöler curve model show lower operating costs than the ones obtained with the semi-empirical model. This issue is directly related to a larger BT lifetime estimation from the Whöler curve based ageing model for each of the hybrid ESS size solutions. However, it should be noted that further from the hybrid ESS sizing, the control parameters are independently optimized in both simulations, which also affects how the hybrid ESS is utilized, thus modifying BT and SC lifetime and the shape of the operating cost surface.

In both cases, it can be observed that in general terms increasing the ESS size imply increasing the operating costs. This fact suggests that the additional costs from using a larger ESS are not compensated by the economic savings from increasing BT and/or SC lifetime. However, as the annualized cost of replacements is discretized both for BT and SC according to equation (16), discontinuities are recorded when a change in the number of replacements is calculated from the predicted BT and/or SC lifetime. This effect can be observed *e.g.* in the range of 3.5-4.5 kWh of SC storage in Figure 6a or in the ranges from 20-25 kWh and 25-30 kWh of BT storage in Figure 6b.

In Figure 7 the five optimal solutions obtained for each ageing model are summarised, expressing the different cost components of equation (12). Considering that the main objective is to minimize total operating costs of the tramway, the first solution in Figure 7 (from results obtained with each ageing model) was selected as the overall optimal one for this scenario, which coincides with the sizing values highlighted with a data tip in Figure 6. Note that for overall optimal sizing values calculated with each ageing model, the BT size is the same (12.14 kWh), and the difference in the hybrid ESS sizing resides only on small differences in the SC pack size (2.16 kWh for the Whöler curve based model and 1.62 kWh for the semi-empirical model). However, despite the BT pack size is the same, and even taking into account that BT costs suppose only *c.a.* 15% of total operating costs, significant differences are recorded regarding the total operating costs of each solution. The main reason for such a significant difference was considered to be caused by the lifetime prediction obtained with each BT ageing model, which suggests a BT lifetime overestimation from the Whöler curve based ageing model. Additionally, the differences on the cost component relative to the SC pack arise from differences in the calculated optimal size of the pack, and not from the SC performance itself.

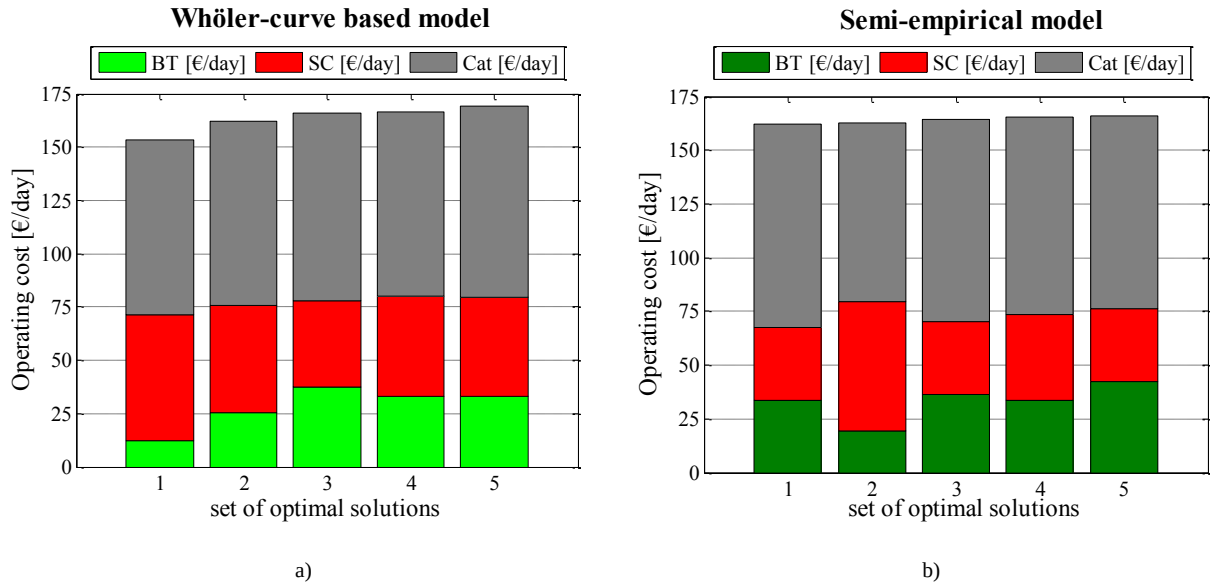


Figure 7: Five optimal results a) Whöler curve based model and b) Semi-empirical model.

The semi-empirical ageing model approach was considered to be reliable for real battery ageing assessment, since the model was validated with very low prediction error (1.4% RMSE) [9]. This way, if the two considered models are compared, the Whöler curve based ageing model tends to overestimate BT lifetime. For this reason, each of the five optimal solutions obtained from the optimization with the Whöler curve based ageing model was re-evaluated using the semi-empirical model. The purpose of the re-evaluation was to compare such model estimations with realistic ageing behaviour and to assess the influence of lifetime overestimations in overall costs assessment. As it can be observed in Figure 8, the BT operating costs calculated in this re-evaluation stage are considerably larger for each of the five optimal solutions. This is conclusively due to differences in the BT useful lifetime estimation, which would mean unexpected BT operating costs of up to *c.a.* 3 times larger for the overall optimal solution calculated with the Whöler curve based model (solution 1).

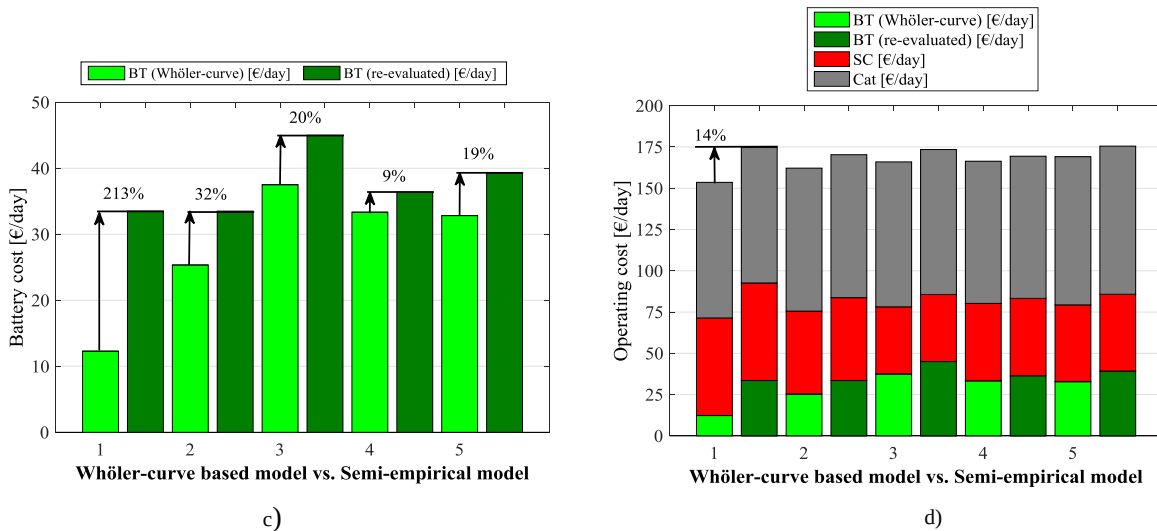


Figure 8: Re-evaluation with the semi-empirical model of the costs calculated for each of the five optimal solutions obtained with the Whöler curve based ageing model: a) BT costs and b) total operating costs.

According to the results shown in Figure 7 and Figure 8, the operating costs of the ESS optimized with the Whöler curve based model would increase up to 14% to 174,81 €/day when implemented on a real tramway

application, while the optimal solution calculated with the semi-empirical model would cost 161,9 €/day, Figure 6. In consequence, when considering an accurate ageing model for BT sizing, savings of 12,91 €/day can be achieved for the case study considered, which would suppose total savings of c.a. 47.000 € for a tramway application with 10 years of lifetime.

Although the savings (in €/day) only represent a small percentage of the total costs of the hybrid ESS (c.a. 8%), the economic impact of accurately predicting battery ageing behaviour over the lifetime of a single tramway system might justify the economic effort required to develop a semi-empirical ageing model. Moreover, inaccurate battery ageing prediction would suppose unscheduled battery replacements, which may also increase the maintenance costs of the system.

6 Conclusions

The sizing methodology presented in this paper represents a comprehensive approach to hybrid ESS sizing, including detailed modelling of the application, energy management strategy, ESS and costs components of the whole system.

ESS sizing and overall costs results show significant impact of the battery ageing model on ESS sizing. Even considering that the batteries suppose c.a. 15% of the total energy costs of the tramway application (for the optimal solutions considered), calculating the optimal sizing with the semi-empirical ageing model can produce savings of up to 8% when compared to the real costs of the optimal sizing solution calculated with a Whöler curve based ageing model (calculated after BT lifetime re-evaluation). In any case, it is worth mentioning that the accuracy of Whöler curve based models is not constant over the whole DOD range, and especially at low DOD region (large BT size) this kind of ageing models tend to significantly overestimate ESS lifetime. In applications in which large number of micro-cycles are frequent, the use of more advanced ageing models (e.g. the semi-empirical ageing model) is advisable.

Precision on battery ageing evaluation can also contribute to better evaluate hybrid ESS capability to fulfil the daily operation profile once the batteries are degraded, which might also suppose discarding some of the SC and BT sizing combinations. Such analysis was only possible due to the iterative method implemented with the semi-empirical ageing model.

Further steps include replicating the analysis with more advanced electrical models both for BT and SC that allow better assessing the energy and power capabilities of each hybrid ESS sizing solution calculated. However, preliminary evaluation showed that the impact of the electric model is considerably less relevant for sizing purposes than the impact of the ageing model. Extending the analysis to other applications in which battery costs suppose a larger share of total system costs is also foreseen.

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