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SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

Executive Summary of the Thesis

Battery Electric Bus: a technical and economic simulation framework for battery aging assessment

Laurea Magistrale in Mobility Engineering - Ingegneria della mobilità

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1. Introduction

Pollution represents a major threat to both human health and the environment. In Europe, one in every eight deaths is linked to pollution [1], while greenhouse gas (GHG) emissions have driven a significant increase in global mean temperatures since the pre-industrial period [2]. The transport sector is the second-largest contributor to GHG emissions [3] and a major source of local pollutants [4], making it a key area of intervention to reduce global emissions and mitigate global warming. For this reason, the European Union has promoted a progressive transition from Internal Combustion Engine (ICE) vehicles to zero-emission solutions, identifying Electric Vehicles (EVs) as one of the most promising technologies to achieve climate neutrality targets. This transition is not limited to private mobility but increasingly involves public transport systems, where Battery Electric Buses (BEBs) are progressively replacing conventional diesel fleets. However, the large-scale adoption of BEBs introduces new operational and technical challenges for Public Transport Operators (PTOs). In this context, two main challenges arise:

1. **The charging scheduling problem**: unlike conventional buses, which can be refuelled in a few minutes, BEBs require significantly longer charging times. As a consequence, charging activities must be carefully planned to ensure service continuity, optimal infrastructure utilization, and cost-effective energy management.
2. **The battery management problem**: differently from a fuel tank, a battery is a degradable component whose lifetime is strongly influenced by charging patterns, therefore it is necessary to understand which charging strategies can extend its useful life and how to estimate its State of Health (SoH).

Within this context, this thesis, developed in collaboration with Autoguidovie S.p.A., proposes a simulation-based methodological framework aimed at supporting PTOs in the evaluation of charging strategies. The developed tool enables the analysis of the impact of operational charging choices on battery degradation, infrastructure requirements, and energy-related costs, thus providing decision support for economically and technically optimized fleet electrification.

2. State of the art and literature review

This chapter reviews the state of the art in battery aging modeling and its integration within Electric Bus Scheduling Problem (EBSP), with the aim of identifying the main limitations of existing approaches and defining the research gap addressed in this thesis.

Battery degradation is driven by two primary mechanisms:

- **Calendar aging**, which occurs when the battery is at rest, a condition common during overnight parking.
- **Cycling aging**, associated with repeated charge-discharge cycles, particularly relevant in BEB operations where batteries experience intensive daily use.

The combined impact of these mechanisms leads to capacity and power fade, determining the evolution of the battery SoH. Battery aging results from multiple underlying mechanisms, each influenced by operating conditions and aging factors. Figure 1 provides an overview of these mechanisms, illustrating their causes and the associated degradation modes.

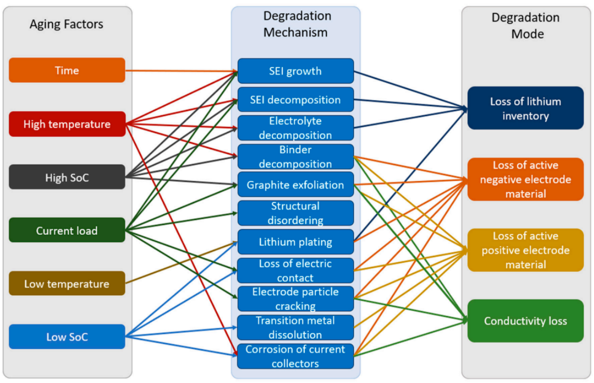

Figure 1: Factors affecting aging, chemical and physical mechanisms, and the effects they cause [5].

Numerous aging models have been proposed to predict battery degradation as a function of operating conditions. However, many approaches focus only on cycling degradation or oversimplify calendar aging. When embedded in EBSP formulations, battery lifetime is often treated as a fixed parameter or only partially linked to charging strategies.

A review of the literature reveals several recurring limitations. Not all models simultaneously account for cycling and calendar aging, resulting in incomplete degradation estimations. The primary objective is not always defined in terms of total system cost, which should include charging costs, battery degradation costs, capital expenditures, and residual value. Many formulations assume simplified charging-discharging patterns that do not reflect the variability of real BEB operations, characterized by heterogeneous routes, partial charging events, and rest periods at different State of Charge (SoC) levels. Furthermore, although cell balancing is widely recognized as essential for safe operation and long battery lifetime, most aging-aware EBSP models do not explicitly incorporate balancing constraints. Some proposed strategies limit the SoC operating range without considering that passive balancing systems require periodic high SoC levels to function properly, making such strategies theoretically optimal but technically infeasible.

These limitations highlight the need for a modeling framework that integrates realistic operational conditions, comprehensive aging representation, cost optimization, and balancing requirements, bridging the gap between theoretical battery aging models and practical fleet management applications.

3. Model presentation

The methodological framework developed in this thesis addresses the research gap identified in the literature review. It is structured around four main models, which interact with each other as illustrated in the workflow shown in Figure 2.

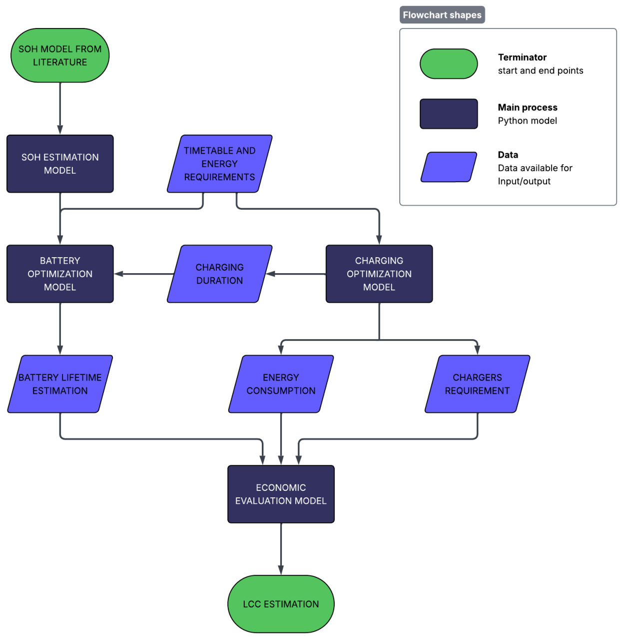

Figure 2: Workflow of the models implemented in this thesis.

3.1. SoH Estimation Model

For the creation of the SoH Estimation Model, the battery aging model presented by the authors in [6] has been selected as the starting point. This model, developed for Nickel Manganese Cobalt oxide (NMC) batteries, considers both calendar and cycling aging components and incorporates dependencies on temperature, average voltage and Depth of Discharge (DoD), as shown in Equations 1 - 2 - 3.

$$C = 1 - \alpha_{\text{cap}} \cdot t^{0.75} - \beta_{\text{cap}} \cdot \sqrt{Q} \tag{1}$$

$$\alpha_{\text{cap}} = (7.534 \cdot V - 23.75) \cdot 10^{6}\, e^{-\frac{6976}{T}} \tag{2}$$

$$\begin{aligned}\beta_{\text{cap}} = 7.348 \cdot 10^{-3} \cdot (\overline{V} - 3.667)^2 \\ - 7.600 \cdot 10^{-4} + 4.081 \cdot 10^{-3} \cdot \text{DoD}\end{aligned} \tag{3}$$

In these formulations, t is the cumulative resting time expressed in days and Q is the cumulative charge throughput expressed in ampere-hours.

To better reflect current battery technologies, the model has been calibrated using two correction factors: c_{cal} which normalizes the effect of cell capacity, and γ, which aligns the predicted lifetime with the observed performance of modern battery systems. This calibration procedure leads to an upgraded formulation, reported in Equation 4, enabling consistent and realistic estimation of degradation for modern NMC batteries.

$$C = 1 - \gamma \left(\alpha_{\text{cap}} \cdot t^{0.75} + \beta_{\text{cap}} \cdot \sqrt{c_{\text{cal}} \cdot Q} \right) \tag{4}$$

3.2. Battery Optimization Model

The SoH Estimation Model, as well as the other mathematical models considered, can be applied only under constant operating and resting conditions. To overcome this limitation, a Python-based simulation tool has been developed.

The Battery Optimization Model integrates the mathematical formulation provided by the SoH Estimation Model with periodic phenomena commonly occurring in real-world operations, such as rest days, annual maintenance downtime, and battery balancing events. This approach enables an accurate representation of operational conditions and allows the simulation of SoH evolution over time.

In the Python-based simulation tool, five different scenarios are implemented. The first scenario represents the reference case, reflecting a typical operational profile commonly adopted by transport operators without any form of optimization. The remaining scenarios correspond to alternative charging strategies designed to extend battery lifetime. Table 1 provides an overview of the optimization elements included in each scenario. Three main aspects are considered:

- **SoC optimization**, which refers to the application of a dedicated algorithm to determine the optimal operating SoC range.
- **DoD reduction**, which consists in splitting the required daily energy into multiple charging events in order to reduce battery stress.

- **Delayed charging**, which indicates that the charging process is postponed so as to finish just before the next operational period.

Scenario	SoC Optimization	DoD Reduction	Delayed Charge
BASE	×	×	×
START	✓	×	×
END	✓	×	✓
START-SPLIT	✓	✓	×
END-SPLIT	✓	✓	✓

Table 1: Overview of the charging strategy scenarios and enabled optimization features.

Several Python functions have been developed to support the Battery Optimization Model and ensure its consistency with real-world applications. The final output of this tool consists of both graphical and numerical comparisons of the expected battery lifetime under the five simulated scenarios. This enables the user to clearly understand the implications of adopting one charging strategy over another.

3.3. Charging Optimization Model

Charging schedules must be carefully planned and managed, as the EBSP represents one of the most critical aspects of BEB operations. While extending battery lifetime is important, the ultimate objective for transport operators is the minimization of total costs over the vehicle lifetime. Therefore, focusing exclusively on battery degradation without considering infrastructure and energy costs would provide only a partial evaluation of charging strategies.

For this reason, a dedicated Charging Optimization Model has been developed in parallel with the Battery Optimization Model. This model generates feasible charging schedules under realistic operational constraints and computes the key parameters required for the subsequent economic assessment. It has been implemented in Python using a constraint programming approach, which enables the identification of optimal charging solutions based on the operational input data.

The optimization algorithm assigns time slots, chargers, and power levels to each bus while respecting the constraints imposed by the selected charging strategy. Its primary objective is to minimize the number of chargers required to meet the fleet energy demand, thereby reducing infrastructure investments. A secondary objective promotes longer charging sessions, encouraging lower charging power, which is associated with improved battery health.

Due to the high computational complexity of the problem, characterized by numerous binary decision variables and interdependent constraints, specific strategies have been implemented to reduce the search space and improve computational efficiency, including symmetry-breaking techniques.

Overall, the model enables to verify the operational feasibility of the proposed charging strategies, while providing the essential inputs for the economic analysis. In particular, it determines the minimum number of chargers required and the daily energy distribution across tariff periods, which are key parameters for assessing both infrastructure and operational costs.

3.4. Economic Evaluation Model

The Battery Optimization Model and the Charging Optimization Model provide all the key parameters required to compare the different charging strategies from an economic perspective. In particular, the battery degradation trends, the number of chargers required, and the energy consumption in each tariff period are used as inputs for the final evaluation.

To perform this comparison, a dedicated Economic Evaluation Model has been developed in Python. The model estimates the total cost associated with each scenario over the vehicle lifetime by adopting the Life Cycle Cost (LCC) as the reference performance indicator. This metric enables the simultaneous assessment of capital and operational expenditures, ensuring a comprehensive comparison of alternative charging strategies.

In order to preserve the focus on the differences among scenarios, only cost components affected by the charging strategy are included in the analysis. These consist of infrastructure investments, battery replacements, electricity costs, and charger maintenance. Components that remain identical across all scenarios are excluded, as they do not influence the relative comparison.

A key aspect of the model is the inclusion of battery residual value, which reflects the potential reuse of retired batteries in second-life stationary storage applications. The value of the retired batteries has been modeled as a function of the battery's actual SoH at the moment of retirement, rather than assuming a fixed residual value, in order to provide more accurate estimation.

Given the uncertainty associated with the lifetime of electric buses, three different analysis horizons have been considered, representing pessimistic (12 years), moderate (16 years), and optimistic (20 years) scenarios. For each case, the model computes the discounted cash flows and the corresponding LCC.

Finally, the results are aggregated and visualized to enable a clear comparison of the different charging strategies in terms of total cost and cost breakdown, including batteries, chargers, and energy. This model therefore provides a comprehensive framework to support decision-making, allowing operators to identify the most cost-effective battery management strategy.

4. Practical application and results

A real-world case study is presented to demonstrate the practical implementation of the proposed framework. This allows the model to be tested under realistic operating conditions, assessing its effectiveness and robustness, and provides a basis for discussing the results and insights.

4.1. Case study

The analyzed case study concerns the application of the developed models to the electric bus fleet operated by Autoguidovie S.p.A. in the province of Cremona. The fleet consists of nine Iveco E-Way battery electric buses: five 12-meter vehicles deployed on interurban and suburban routes within the province, and four 9-meter buses mainly employed on the urban network of Crema.

The bus blocks analyzed in this study are based on real operational schedules provided by the operator and combined with an estimation of the energy demand of each shift derived from real consumption data. This approach enables a clear and concise representation of each bus block in both temporal and energetic terms.

4.2. Application of the Battery Optimization Model

The Battery Optimization Model has been applied to the bus blocks described in the previous section in order to simulate battery aging under realistic operating conditions. By exploiting the detailed temporal and energetic information associated with each duty cycle, the model reconstructs detailed SoC profiles over time and generates the corresponding SoH evolution curves.

To ensure consistency with real-world operations, several operational assumptions have been introduced, including the rotation of bus blocks among vehicles, weekly rest days, annual downtime periods, and seasonal schedule variations between the school and non-school service periods, which are associated with different operating temperatures. In addition, periodic full charges are considered to represent balancing procedures performed to maintain battery reliability.

The five battery management scenarios have been analyzed, and the results show that the considered strategies lead to significantly different aging behaviors, highlighting the strong impact of operational and charging practices on battery lifetime. Moreover, relevant differences between 12-meter and 9-meter buses have been observed, mainly due to the distinct structure of their duty cycles and Depth of Discharge profiles. Nevertheless, for both vehicle groups, the optimized scenarios, and in particular the End-Split scenario, enable a substantial extension of the expected battery lifetime.

The SoH evolution for 12-meter and 9-meter buses is reported in Figure 3 and Figure 4, respectively. The degradation trends are clearly non-linear and exhibit a certain degree of irregularity. This behavior is mainly caused by the alternation of seasonal operating conditions and temperature variations, which strongly influence the underlying aging mechanisms.

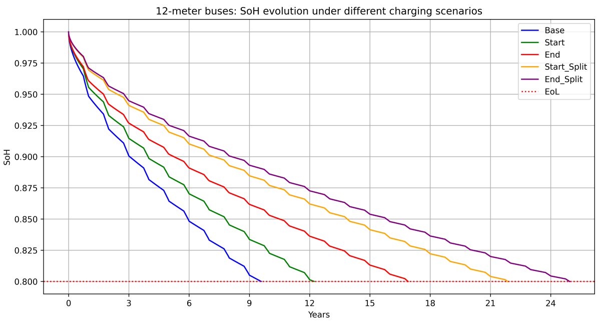

Figure 3: Evolution of battery SoH over time for the different charging scenarios for the 12-meter buses.

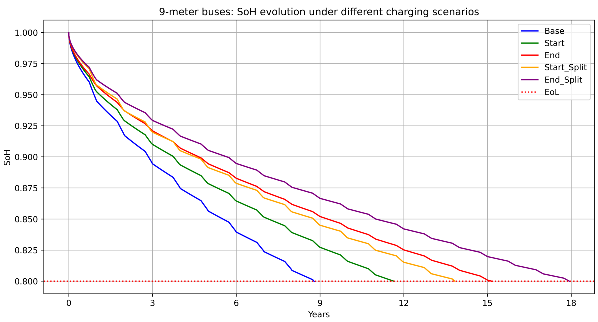

Figure 4: Evolution of battery SoH over time for the different charging scenarios for the 9-meter buses.

4.3. Application of the Charging Optimization Model

The application of the Charging Optimization Model demonstrated the operational feasibility of the proposed charging strategies. The model has been applied to the five scenarios under both school and non-school operating conditions, generating a total of ten charging timetables. For each case, the model provides the associated energy consumption in the different tariff periods and the minimum number of chargers required to meet the fleet energy demand.

The optimization algorithm implemented in the Python script may require significant computational effort. In some scenarios, the solution time exceeds 80 minutes. Nevertheless, the model proved to be robust and effective, as it was able to identify an optimal charging solution for all the analyzed cases.

In the considered case study, charging operations take place at the depot located in Cremona, which is equipped with 150 kW chargers, each provided with two plugs. When a single plug is used, the charger can deliver its full rated power, whereas when both plugs are simultaneously occupied, the available power is equally shared between the two buses.

Figure 5 reports one of the generated charging timetables, namely the one associated with the End-Split scenario during the school period. This graphical representation includes all the relevant scheduling information and allows the temporal allocation of chargers to be clearly visualized. Simultaneous connections to the same charger are highlighted using lighter color shades, while the specific plug assigned to each charging event is indicated alongside the corresponding charging slots.

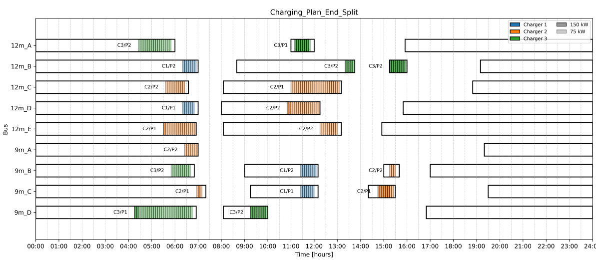

Figure 5: Gantt chart illustrating the optimized charging schedule of the fleet in the End-Split scenario under school period operation.

4.4. Application of the Economic Evaluation Model

The outputs of the previous models are used in this final Python script to compute the Life Cycle Cost for each analyzed scenario. Each scenario is evaluated under three bus lifetime assumptions: pessimistic, moderate, and optimistic, resulting in a total of fifteen LCC assessments.

Regarding energy expenditures, the model accounts for the operation of each bus under both school and non-school schedules, which differ in energy demand and in the temporal distribution of charging activities. For each scenario, the number of chargers is set to the maximum required to meet energy demand and operational constraints across both schedules, ensuring feasibility under the most demanding conditions.

Once the LCCs are computed, the scenarios can be compared across the different time horizons. Table 2 reports the LCC and its main components for the pessimistic lifetime assumption. In some scenarios, the battery-related component of the LCC is negative, indicating that revenues from the sale of retired batteries exceed the costs of replacements. This is due to the fact that the initial cost of new batteries, together with the bus purchase cost, is not included in the analysis, as it is identical across all scenarios. This approach allows the comparison to focus exclusively on cost differences arising from the adopted charging and battery management strategies.

Scenario	Energy	Chargers	Batteries	Total LCC
BASE SCENARIO	707 715 €	138 170 €	21 017 €	866 902 €
START SCENARIO	702 514 €	92 114 €	-80 627 €	714 001 €
END SCENARIO	609 541 €	184 227 €	-130 556 €	663 212 €
START-SPLIT SCENARIO	691 999 €	138 170 €	-134 007 €	696 162 €
END-SPLIT SCENARIO	650 921 €	138 170 €	-138 353 €	650 738 €

Table 2: Total LCC and the breakdown into energy, chargers, and battery costs for each charging scenario under the pessimistic bus lifetime assumption (12 years).

The data in Table 2 are used to generate the graphical representation in Figure 6, enabling an intuitive comparison among scenarios. The results show that, compared to the Base Scenario with no optimization, the operator can achieve savings of up to approximately 200 000 € over the fleet's lifetime. Differences among the four optimized scenarios are smaller, highlighting that the choice of one charging strategy over another is not primarily driven by the extension of the battery lifetime guaranteed by each scenario, but rather by the costs associated with the charging infrastructure and, most importantly, by energy expenditures, whose contribution to the overall LCC has been shown to be predominant.

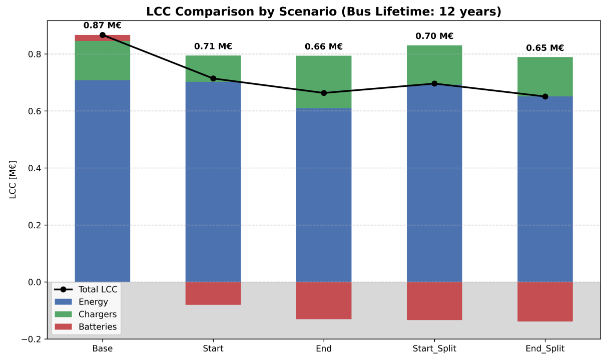

Figure 6: Graphical representation of the total LCC and its components for each charging scenario under the pessimistic bus lifetime assumption.

Similar trends are observed for the moderate and optimistic lifetime assumptions. Overall, the analysis demonstrates that the relationship between battery lifetime extension and total LCC is not linear. Consequently, a scenario that maximizes battery lifespan should not be adopted a priori without considering its impact on energy and charging infrastructure costs.

5. Conclusions and future developments

The methodological approach presented in this thesis enables the application of theoretical SoH estimation models to real-world situations. This has been achieved through the development of a Python environment in which the PTO can input its specific technical and operational data, allowing tailored SoH estimations under different operational conditions.

A key feature of this work is its easy upgradability: the underlying mathematical model can be replaced with an alternative that better reflects the specific situation, while the overall methodological approach and simulation environment remain fully functional. Moreover, the charging optimization algorithm developed provides a flexible tool to generate efficient BEB charging schedules in any operational context, with applicability beyond the present study.

Finally, the results highlight that extending the useful life of BEB batteries is only a minor aspect within the broader framework of fleet cost optimization. While longer battery life reduces replacement costs, other factors, particularly energy expenditures, have a far stronger impact on the overall economic benefits achievable by a PTO when adopting a given charging strategy.

5.1. Future developments

Future developments could focus on integrating the presented Python models into a single optimization algorithm to identify the charging strategy that minimizes the overall Life Cycle Cost of the fleet. While this would represent a valuable advancement, it would require substantial computational resources. The current algorithm, designed to minimize the number of chargers, is already computationally intensive, and including all LCC components would exceed the capabilities of a standard personal laptop. Implementation on more powerful computing platforms could enable comprehensive analyses and provide a significant contribution to this field.

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