Li-ion Battery Aging Conscious Intelligent Energy Management Strategy for Hybrid Electric Buses

Estrategia inteligente basada en envejecimiento de la batería de litio-ion para la gestión energética de autobuses híbridos eléctricos

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Abstract— This paper aims to propose a battery aging conscious energy management strategy. The initial design of an energy management strategy is a significant point to fulfill the efficiency goals in the short term. However, with aging, the initial conditions may vary. The new trend of digitalization allows monitoring the operation, having the possibility to improve the performance of the initially proposed strategy in the long term. Therefore, a methodology for updating the energy management strategy along the bus lifetime is intended to improve the operating costs and extend the battery lifetime. This methodology is based on a dynamic programming optimization, tuning the membership functions in a fuzzy logic control. The simulation results show a reduction of the operation costs up to 47% as long as it stands for battery (BT) lifetime extension of around 2.94%.

***Keywords*— Energy management, dynamic programming, fuzzy logic, hybrid electric bus, state of health, energy storage systems.**

Resumen— El objetivo de este trabajo es proponer una estrategia inteligente basada en el envejecimiento de la batería de litio-ion instalada abordo de vehículo como aplicación de gestión energética. El diseño inicial de una estrategia de gestión energética (EMS) es un paso significativo para cumplir los objetivos de eficiencia en la operación a corto plazo. Sin embargo, debido al envejecimiento de la batería las condiciones iniciales de la EMS pueden variar. La nueva tendencia hacia la digitalización permite monitorizar la operación, brindando la posibilidad de mejorar el desempeño de la estrategia inicialmente propuesta en el largo plazo. Por lo tanto, se propone una metodología para actualizar la EMS con el objetivo de mejorar los costos de operación y extender la vida útil de la batería. La metodología se basa en una optimización mediante programación dinámica para parametrizar las funciones de pertenencia de un control difuso. Los resultados de simulación muestran una reducción en los costos de operación entorno al 47 % junto con una extensión de la vida útil de la batería de alrededor de 2.94 %.

***Palabras Clave*— Gestión energética, programación dinámica, lógica difusa, autobús híbrido eléctrico, estado de salud, sistema de almacenamiento de energía.**

I. Introduction

Nowadays, urban transport is undergoing a fundamental shift to greener and more sustainable solutions. This evolution has been driven by two main factors, a growing awareness of the emitted pollution, especially in urban areas and the lithium-based batteries (BTs) price decrease (nearly 79% since 2010 [1]). However, the implementation of hybrid and electric buses is a challenging process due to the high investment cost besides conventional buses.

Some studies pointed out the influence of the BT price on the buses total cost, reaching values of the 39% [2]. Adding the fact that BTs have a shorter lifetime than power electronic systems, the BT system is identified as a bottleneck in the lifetime of the bus. Moreover, that BT pack replacements are required, this affects significantly to the operation costs during the vehicle lifetime [3], [4], increasing the total cost of ownership (TCO). Therefore, it can be said that the BT lifetime is closely related to vehicle operation.

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For bus manufacturers, the developed initial energy management strategy (EMS) for fulfilling the efficiency operation goals is a significant point. However, the conditions used for the initial EMS vary throughout the bus lifetime. Therefore, an update of the initial EMS will adjust the EMS to the new situation. For the correct update of the EMS, the continuous operation monitoring is needed. This need is fulfilled with the latest vehicles digitalization trend, which allows the constant monitoring of the operation. Consequently, having the possibility to analyze the current operation and take action to correct it.

The operation information with the needed BT advance knowledge will allow managing the BT lifetime, going a step further on the EMS. In this regard, new techniques for managing the BT aging are needed, since BT replacements are directly related to the TCO. Consequently, the operation management conscious of the BT aging will allow improving the TCO further. As a result, they are making urban mobility electrification a more attractive and viable solution for investors.

Dealing with hybrid propulsion systems, several EMSs have been proposed in the literature with a multi-objective strategy to minimize fuel consumption and at the same time minimize the capacity loss and extend the BT lifetime [5], [6]. It has been underlined that these strategies do not consider the state of health (SOH) of the BT as an input. The SOH is a piece of valuable information, which enables the maximization of the BT lifetime in a long-term scope.

The SOH enables to act to manage the BT lifetime in a long term scope. In [4], Du J. *et. al* propose an EMS for an hybrid electric bus (HEB) with a hybrid energy storage system (HESS), to minimize the BT degradation and total costs. However, this minimization process is based on the power management of the HESS, without any updates of the EMS within the bus lifetime.

This paper aims to develop a BT aging conscious intelligent EMS focused on imporving the BT lifetime. In the first part, a fuzzy logic (FL) algorithm is developed based on the short term EMS initially designed. This strategy is tuned by using the optimal operation obtained by dynamic programming (DP) optimization. This strategy is tuned based on the optimal operation obtained by dynamic programming (DP) optimization. As the initial conditions vary and the BT capacity fades, a methodology for updating the EMS is proposed, to maximize the BT aging and improve the operating costs. Operation costs improvements up to 47% are obtained beside a rule-based strategy, and a BT lifetime extension of 2.94% is reached.

II. Scenario Overview

The scenario analyzed in this paper is based on a series hybrid electric bus (SHEB) that performs in an urban route. As shown in Fig. 1, this type of bus power-train is pulled by an electric motor (EM). In this configuration, the required power is provided by a genset (GS, composed by an internal combustion engine (ICE) coupled to an electric generator) and a BT pack.

The parameters of this scenario are listed in Table I [7].

Simulation in MATLAB has been performed. For this simulation, line 28 from Donostia-San Sebastian (Spain) urban bus route has been used. It is worth to highlight that the BT used in this SHEB is fast charged after every round-trip, except for the last round-trip, which is depot charged. The driving profile is depicted in Fig 2.

III. Battery Aging Conscious Intelligent Energy Management Strategy

The suitable and efficient power split among the GS and BT became a complex problem. There are several factors to take into account to minimize fuel consumption. Furthermore, if BT aging management is included in the problem, it becomes even more complex. To answer this problem, advanced techniques and knowledge of the BT and application are needed, as a fair trade between the fuel consumption minimization and the BT utilization management has to be determined.

In this context, FL rule-based EMS has been considered as the technique to deal with the complex problem. The main reason for using FL has been the capacity of this technique to adapt to the uneven events during the real operation, due to the non-linear variable response depending on the operation conditions [7].

Therefore, a FL based BT conscious EMS has been proposed. In the following subsections the proposed EMS FL membership functions, optimization used for

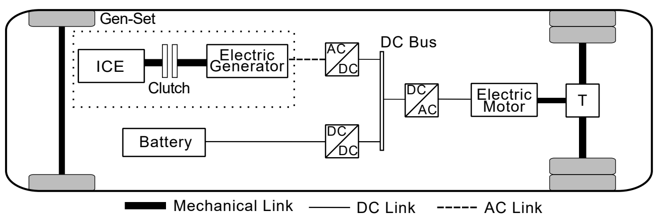

Figure 1: Series HEB configuration.

Table I: Scenario approach.

Elements		Units	Parameters
Electric Motor Power		kW	196.5
Genset Power		kW	160
Battery Pack	Voltage	V	650
	Energy	kWh	24

the tuning and the output are described. In Fig. 3 an overview of the proposed FL EMS is shown.

A. Fuzzy Logic Membership functions

The proposed FL controller have been based on a Sugeno Fuzzy Inference System [8], due to the less processing needed time. The utilized membership functions are detailed in Fig. 4. The names of the membership functions have been defined as follows:
- GS power ($P_{GS}(k-1)$ $[W]$): the input data is the previous GS power value, to avoid sudden GS power demands.
- Regeneration capability (P_{Regen} $[W]$): the input data is the difference between the maximum BT charging power and the regenerated power in the continuous bus, to maximize the BT regenerative charging.
- DC link power balance (P_{DCLink} $[W]$): the input stands for the power balance of the continuous bus, to evaluate the power demand
- BT State of Charge (SOC): the input is the current SOC of the BT, to evaluate if the BT needs to be charged or discharged.

B. Fuzzy Logic Tuning

The tuning of the proposed EMS has been based on both advance application knowledge and an off-line optimization of the driving profile. The DC link power balance [W], GS Power [W], and Regeneration capability [W] membership functions have been tuned based on the advanced application knowledge. On the contrary, the SOC [%] has been adjusted based on the optimal operation obtained from DP optimization.

The predefined driving profile has been optimized based on DP optimization. The optimization problem is based on the following cost function (J), for the fuel consumption minimization [9]:

$$J = \sum_{i=0}^{N-1} \triangle m_f(U(i)) \cdot T_s \tag{1}$$

where $\triangle m_f \cdot T_s$ is the fuel mass consumption at each time step (T_s=1 s), determined by the split factor (U), within the urban route length (N) [10]. Therefore the optimized parameter is the split factor.

In the SHEB configuration, the split factor stands for the division of the power demand (P_{dem} $[W]$) among the GS (P_{GS} $[W]$) and the ESS (P_{ESS} $[W]$).

$$P_{dem}(i) = \begin{cases} P_{GS}(i) = P_{dem}(i) \cdot (1 - U(i)) \\ P_{BT}(i) = P_{dem}(i) \cdot U(i) \end{cases} \tag{2}$$

To maximize the BT use obtaining the lowest fuel consumption, the optimization has been designed, to reach a predefined minimum SOC. This minimum SOC has been calculated based on the amount of energy that can be recharged with the available fast charger power in 2.5 minutes.

From the obtained optimal SOC operation, the minimum and maximum SOC values are extracted. These points are used to set the A (minimum SOC) and B (maximum SOC) points, as shown in Fig. 4.

C. Fuzzy Logic Output

The output variable of the proposed EMS is the GS power [W]. In Sugeno Fuzzy Inference System, the output values are defuzzified by statistic functions [11]. The output statistics function used in this design is the weighted arithmetic mean value. Each data point has a degree of contribution, also denominated as weight, on the weighted arithmetic mean calculus. Consequently, for calculating the output, weighted values are required. These weighted values are computed by another mathematical function denominated as the propagation of error, Eq. (3). In this case, the weight refers to the contribution of the FL controller rules (w_{rule_n}) for each GS power value, $w_{GSvalue}$.

$$w_{GSvalue} = \sqrt{w_{rule_1}^2 + w_{rule_2}^2 + ... + w_{rule_n}^2} \tag{3}$$

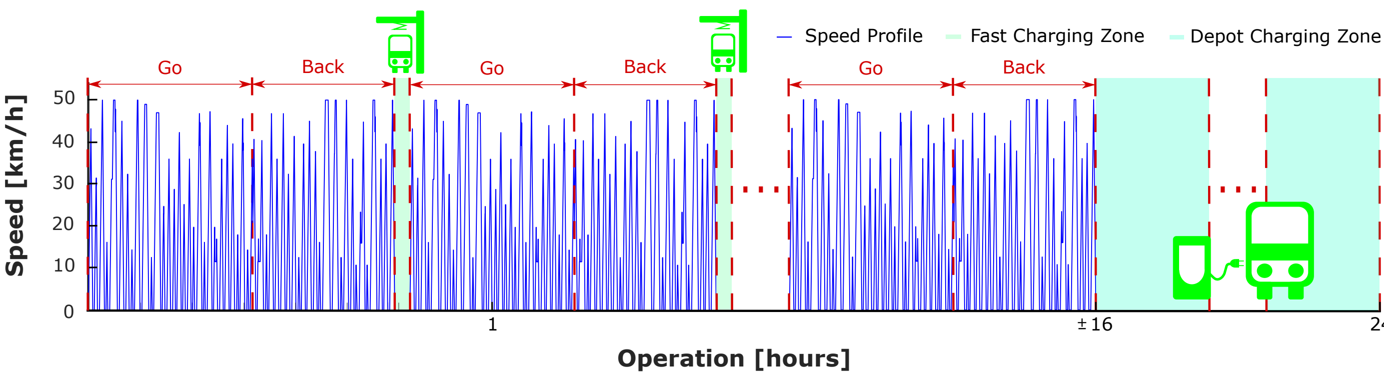

Figure 2: Driving profile.

After obtaining the weighted value, weighted arithmetic means statistics function can be applied to obtain GS (GS_{output}) output value. The following formula is used for the output definition:

$$GS_{output} = \frac{\sum_{i=1}^{n}(w_{GSi} \cdot GS_i)}{\sum_{i=1}^{n} w_{GSi}} \quad (4)$$

where, GS_i $[W]$ are the GS constants, defined by n the number of constants and w_{GSi} represents the weighted value of each constant.

GS_i is tuned based on the obtained DP optimal GS operation values. This tuning is based on extracting the minimum, quantiles 25, 50 and 75, and the maximum values.

IV. EMS Updating Methodology

The complexity of the energy management problem increases as the conditions used for the initial EMS design conditions vary. This initial EMS is a significant point for fulfilling the operation and efficiency goals. However, the state of the bus with the aging differs, identifying the BT as a bottleneck in the lifetime of the bus. For this reason, BT conscious EMS has been proposed.

The BT aging analysis and estimation is also a complex task as it has been aforementioned in Sec. I. This is the main reason for the need of updating the initial EMS. For the correct update of the EMS, the continuous operation monitoring is needed. This will allow to analyze the current operation and take action to correct it.

Therefore, a methodology for updating the EMS to correct the SOH of the BT, fulfilling the operation conditions is presented. The proposed methodology is shown in Fig. 5. For the initial and subsequent EMS

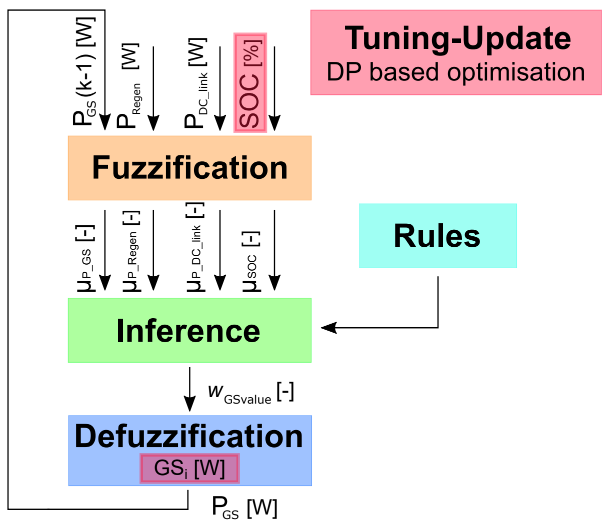

Figure 3: Fuzzy Logic control block diagram.

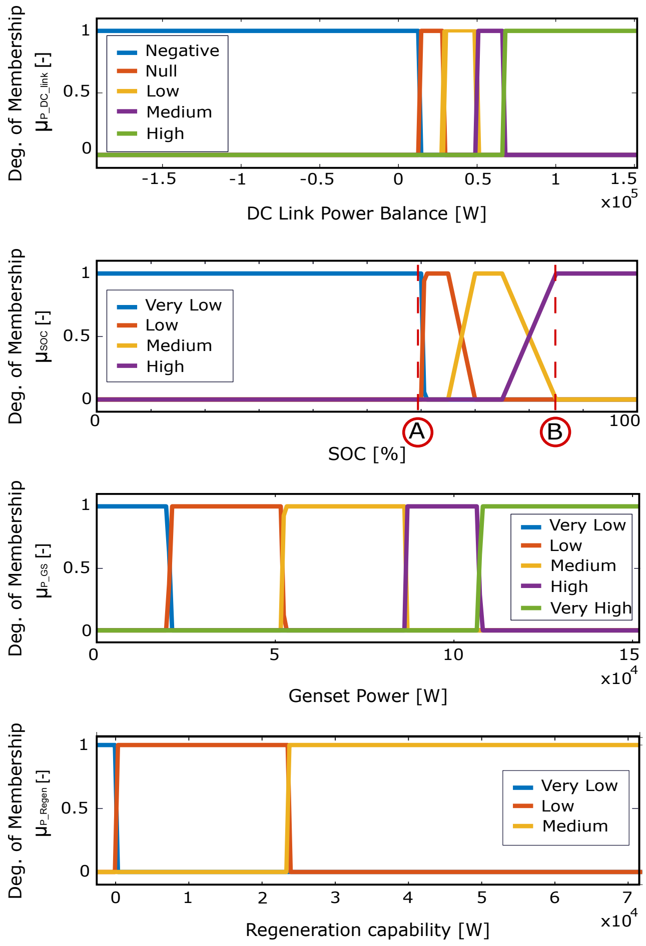

Figure 4: Fuzzy Logic membership functions.

designs, two periods have been set, the short and the long terms subsequently. In the following lines, the methodology stages are presented in detail.

Stage 1: *Driving Profile Operation Optimization*

In the first stage, the *Short Term EMS* design is developed. Thes initial EMS has been designed for fulfilling the operation efficiency goals.

Stage 2: *Urban bus operation*

In this stage, a simulation in MATLAB of the urban bus real operation driving behavior (described in Sec. II) is performed. For the real driving operation conditions, driving disruptions have been considered, such as passenger, auxiliary and traffic disruptions [10]. Additionally, in this simulation, continuous operations monitoring is done during 15 days.

Stage 3: *Analysis and Decision Maker*

This stage consists of analyzing the current aging of the BT and updating the EMS, to improve the operation from the initial EMS design. The continuous operation data gathered in the urban bus operation simulation is processed, and the BT aging is obtained and analyzed. Subsequently, to adapt the new EMS to the new condi-

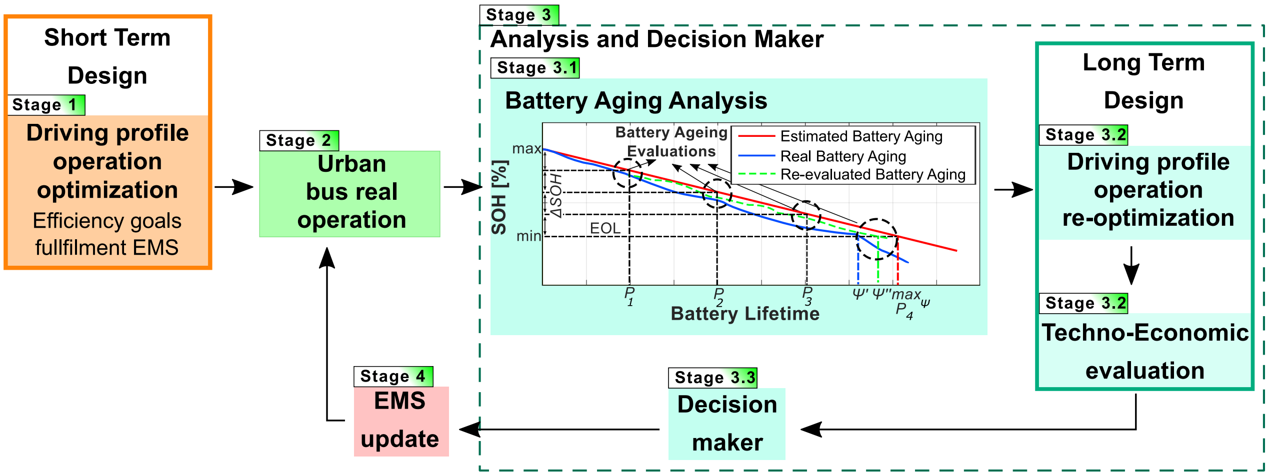

Figure 5: EMS updating methodology.

tions, decisions are made. For that purpose, the following three stages are required:

Stage 3.1: *Battery Aging Analysis*

For a correct BT aging management, apart from advanced BT knowledge, an appropriate BT aging model is needed. BT lifetime estimation is a complex task due to the dependence on multiple stress factors [12]. The literature proposes different aging models, which can be categorized as physiochemical, empirical or semi-empirical with uneven levels of complexity and accuracy [12], [13]. The semi-empirical model is the most widely used method [12]. For this work, a Wöhler curve based fatigue method has been used.

Firstly, both estimated and real aging curves are compared in a determined evaluation period. This evaluation period has been set of steps of 5% of the SOH decrease ($\triangle SOH$) until the end-of-life (EOL) of the BT is reached. In other words, BT aging is evaluated in P_1 95%, P_2 90%, P_3 85% and P_4 80% of SOH. The real aging estimation (blue curve), reaches a lifetime of Ψ'. Consequently, the aging curve varies from the initially estimated one. In this evaluation points, to extend the BT lifetime, there is a need for updating the EMS, to reach Ψ''.

Stage 3.2: *Long Term Design*

To improve the operation obtained from the initial EMS, to determine the most convenient operation. This stage has been divided into two, the driving profile re-optimization and the techno-economic evaluation.

Driving Profile Re-optimization

These re-optimizations consist of modifying the requested charging power from 50 kW to 150 kW by a step of 10 kW. In this way, as the EMS is designed based on the available energy to be recharged (explained in Sec. III-B), the BT utilization will be reduced as the charging power decreases. Consequently, the strategy will increase the GS, improving the BT lifetime. On the contrary, if the BT aging is considered to be as designed, the BT utilization is increased, re-tuning the SOC membership function.

Techno-Economic Evaluation

At this point, the obtained optimization results are techno-economically analyzed. In this outline, the following operating costs are taken into account: fuel consumption cost, BT cost, and BT charging energy cost, Eqs. (5), (6) and (6), respectively.

$$F_{cost} = \sum_{k=1}^{p} \frac{(mf_{ICE}(k) \cdot k_{cs} \cdot C_{L,fuel})}{\rho_{fuel}} \quad [€/day] \quad (5)$$

where ρ_{fuel} is the fuel volumetric density [kg/l], k_{cs} is the global factor to cold starts [-] and $C_{L,fuel}$ [€/l] is fuel, in this case diesel, cost per liter.

$$BT_{cost} = \frac{C_{BT} \cdot E_{BT} \cdot n}{L \cdot O} \cdot \frac{Y_{deg}}{Y_{deg,current}} \quad [€/day] \quad (6)$$

where C_{BT} is the BT cost in [€/kWh], E_{BT} is the BT size [kWh], n are the number of replacements, L is the lifetime operation of the BT [years], O is the yearly operation in [day/years], Y_{deg} are the predicted years and $Y_{deg,current}$ are the current years.

$$\{C_{el} = C_{e,fix} + C_{e,var} \quad [€/day] \quad (7)$$

where $C_{el,fix}$ is the fix power cost in [€/day] and $C_{e,var}$ is the consumed energy cost in [€/day]. Both costs are calculated as follows:

$$\{C_{el,fix} = C_{kW} \cdot P_{cha} \quad [€/day] \quad (8)$$

$$\{C_{el,var} = C_{kWh} \cdot E_{cha} \quad [€/day] \quad (9)$$

where, C_{kW} represents the cost of the charging power, P_{cha} the charging infrastructure power, C_{kWh} the energy cost and E_{cha} the consumed energy from the grid.

The objective of this analysis is to reduce fuel consumption and extend BT lifetime. According to the deviation of the SOH and the techno-economical boundaries, an optimization is selected.

Stage 3.3: *Decision Maker*

In this sub-stage, based on the obtained results form the re-optimization and techno-economic analysis, the most suitable operation will be determined for the *long term EMS* design. For this, a fuel consumption limit has been established, which limits the obtained optimizations results. Therefore, based on the performed techno-economical analysis, the most suitable operation, according to the BT aging, is chosen.

Stage 4 *EMS update*

In this *Long Term EMS*, the selected SOH optimization via DP is used for tuning off-line FL strategy, until the next evaluation period. In the same way as short term EMS, SOC input, and GS output are the adjusted variables. In this EMS operation targets are modified, to correct the BT degradation, obtaining the re-evaluated BT aging curve (green curve, Fig 5). The re-evaluated BT aging maximizes the BT lifetime until point A".

After this design, the EMS is updated to Long Term EMS, and the operation is simulated in MATLAB until the next evaluation period.

V. Results and analysis

To validate the proposed BT conscious EMS and EMS updating methodology, a simulation of the presented SHEB in Section II has been carried out.

In this section, the obtained results are presented. First, the proposed EMS evaluation has been performed. Then, the obtained results from the short and long terms are presented.

A. Proposed EMS evaluation

In Fig. 6 the proposed EMS comparison is shown. The proposed EMS has been first compared against a DP off-line optimization and with the proposed rule-based non-adaptive EMS named LUT (Look up table based EMS) [10]. The operation costs of the proposed approach increase compared to the DP global optimization which has a value of 31.5%. Another comparison is done against the LUT strategy obtaining an increase of 63.7%. Additionally, the obtained operation costs improvement of the proposed EMS compared to the LUT EMS is up to 47%. Indeed, to ensure the adaptability of the proposed approach, a comparison with the maximum demand of auxiliaries and number of passengers on the bus, against

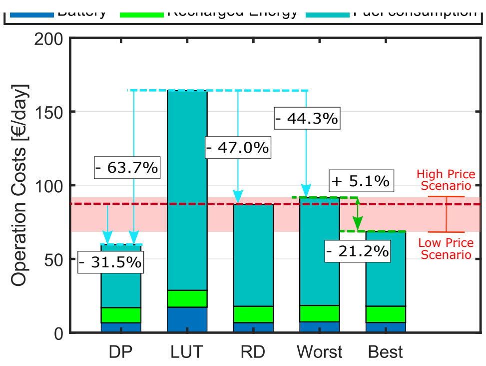

Figure 6: EMS comparison.

the LUT EMS has been done resulting on a decrease of 44.3% of operating costs for the proposed EMS.

For further evaluation and to ensure the stability of the proposed EMS, the worst and best cases have been assessed. The obtained result in the best case, i.e. the bus without passengers and with the minimum of auxiliary consumption, has been a decrease of 21.2%. On the contrary, the worst case has been the evaluation with the maximum of passengers and maximum auxiliary consumption, obtaining an increase of 5.1%.

B. Short and long term evaluations

In this subsection, the proposed methodology for updating the EMS has been analyzed. For this comparison, the non-updated EMS has been defined as the short term ST, and the updated one as the long term LT.

In Fig. 7 the obtained results regarding the BT aging are shown. The BT aging extension for the updated EMS 2.94% against the non-updated EMS. It is noteworthy the BT aging lifetime of the ST, as it does not fulfill the vehicle end-of-life (EOL) planned years. On the contrary, the updated LT EMS overcomes the expected vehicle EOL point. Concerning the BT aging deviation concerning the vehicle lifespan, two scenarios are analyzed. In a first analysis, a unique BT replacement is considered in the whole vehicle life, and the vehicle not reaching EOL is removed before the planned date. The second case study,

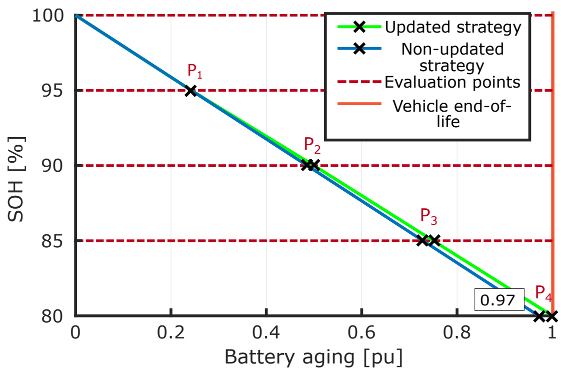

Figure 7: Corrected BT aging

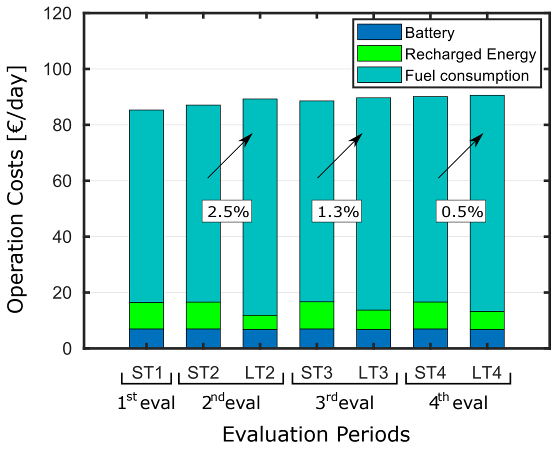

Figure 8: ST and LT comparison with a single replacement.

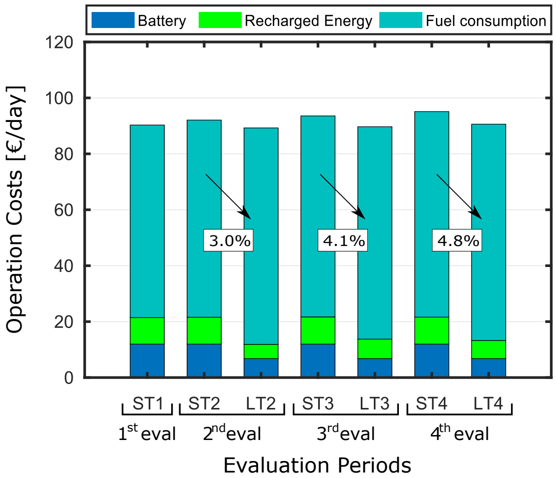

Figure 9: ST and LT comparison with two replacements

for the bus not reaching the vehicle EOL point, a second BT replacement has been considered.

Fig. 8 shows the operation costs obtained on each evaluation point for each EMS, the ST, and the LT. The ST EMS shows lower operation costs than LT EMS, reaching values up to 2.5%.

By contrast, as shown in Fig. 9, if the vehicle requires two BT replacements, the opposite happens. A decrease up to 4.8% in the LT EMS is obtained in the operation costs.

VI. Conclusions

In this paper, a BT aging conscious intelligent energy management strategy was presented focused on BT lifetime maximization. For the validation of the proposed BT conscious EMS and EMS update methodology, a simulation as described in Section II is carried out.

The obtained results against a non-adaptive EMS has been up to 47% of operation costs decrease. For the stability evaluation, the worst and best cases have been evaluated, obtaining an increase of the operation costs up to 5.1% and a decrease up to 21.2% respectively.

The BT aging extension has been of 2.94%, compared to the non-updated EMS, reaching the planned bus EOL. However, in the case of the non-updated EMS, the scheduled EOL date is not reached. In this regard, the two analyzed possibilities are to remove the bus before the planned time or to replace the BT. In the case of removing the bus, the obtained results for the ST operating cost have a decrease up to 2.5%. On the contrary, considering to replace the BT, the operation costs of the LT EMS decrease up to a 4.8%, since the BT lifetime overcomes the planned EOL date and an only BT replacement is needed. It is worth to highlight that the penalization for not reaching the bus EOL was not taken into account for the scenario of removing the bus.

On the ongoing research, an improved and self-adaptive [14] BT aging estimation model will be implemented to the BT aging conscious EMS.

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