Degradation Conscious Dynamic EMS for a Hybrid Energy Storage System Deployed in a Cloud-Edge Based Platform

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***Abstract*— This paper presents an Energy Management Strategy (EMS) designed for a residential building equipped with solar photovoltaic generation and a hybrid battery storage system. The system integrates two batteries: a high-energy and a high-power battery, leveraging their complementary characteristics to optimize energy usage. Three EMS strategies are evaluated: no storage, rule-based control, and optimization-based control, with the latter minimizing operational costs while preserving battery health. A Remaining Useful Life model, based on Gaussian Process, dynamically adjusts operational limits to extend battery lifespan to all the EMSs. A 10-year simulation shows that optimized EMS reduces costs by 24% compared to no storage and 21% compared to the rule-based strategy, and moreover, maintains battery State of Health (SoH) above 80%. The EMS is deployed in a cloud-edge computing platform, ensuring real-time operation and scalability.**

***Index Terms*-- Energy storage, energy management systems, adaptive control, cloud computing, energy exchange.**

I. Introduction

In recent decades, battery-based energy storage has become critically important in a variety of sectors, including transport, consumer electronics and, increasingly, in stationary applications for the energy sector. The increasing integration of intermittent renewable sources, such as solar and wind power, has driven the use of batteries to improve grid stability, reduce dependence on fossil fuels and optimize energy self-consumption [1].

As renewables continue to gain share in the global energy mix, new challenges arise in the efficient management of stored energy. The inherent variability of these sources makes storage key to balancing supply and demand, reducing grid congestion and improving the resilience of the electricity system [2]. However, indiscriminate use of batteries can shorten their lifespan and generate additional costs if not properly managed. Therefore, the development of efficient Energy Management Strategies (EMS) becomes essential to maximize battery performance and reduce operating costs [3]. Various EMS approaches, ranging from rule-based heuristics to advanced optimization techniques, have been proposed to enhance the economic and technical efficiency of energy storage systems. Recent studies highlight that optimization-based EMS can significantly improve cost savings and battery longevity compared to conventional strategies [4–8].

In this work, an EMS designed to optimize the use of energy storage in a complete residential building equipped with solar photovoltaic panels is analyzed. For this purpose, a hybrid storage system composed of two batteries with complementary characteristics is considered: a high-energy (HE) battery, with a capacity of 10 kWh and a maximum power of 1C charge and discharge, and a high-power (HP) battery, with a capacity of 5 kWh and a maximum power of 2C.

The proposed optimization-based strategy is designed to minimize energy costs while maximizing battery lifespan by dynamically adjusting its usage. To evaluate its performance, two additional strategies are considered for comparison: a baseline strategy without storage and a rule-based approach. Both the rule-based and optimization-based strategies adapt charging and discharging rules based on battery degradation and Remaining Useful Life (RUL), ensuring that operational limits evolve over time to prevent excessive wear. The comparison between the different strategies highlights the benefits of a more flexible and adaptive energy management approach, demonstrating how an optimization-driven EMS can achieve significant cost savings while extending battery life.

The article is structured as follows. In Section II, the three evaluated energy management strategies are presented, describing their operating principles and their differences in terms of efficiency and computational complexity. In Section III, the SoH degradation and RUL prediction models used to optimize battery lifetime are detailed. Section IV shows the results obtained in a simulation of ten years of operation, comparing the performance of each strategy in terms of energy costs and battery aging. Section V describes the implementation

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of the EMS on a platform based on cloud-edge computing. Finally, Section VI shows the conclusions obtained from the work performed.

II. Energy Management Strategies

Efficient management of the energy stored in batteries is key to maximizing their cost-effectiveness and extending their lifetime.

The strategies evaluated are as follows:

- Battery-free: energy is bought and sold directly to the grid, without intermediate storage.
- Rule-based: batteries are charged and discharged according to predefined criteria, such as electricity price and State of Charge (SoC).
- Optimization-based: a mathematical approach is used to minimize energy cost while respecting operational and degradation constraints.

In all strategies, energy sold to the grid is assumed to be remunerated at one third of the hourly purchase price as it is nowadays in Spanish tariffs [9]. In addition, the algorithms are informed by the price of electricity for the next day, which allows decisions to be made based on future data and to improve energy management.

Each of these strategies is described in detail below.

A. No-battery strategy

This case represents the baseline scenario, in which no energy storage is available. The energy required by the system is obtained directly from the grid or from currently available renewable sources. If renewable generation exceeds demand, the excess is fed into the grid.

The energy cost in this scenario is calculated as:

$$C_{total} = \left(\sum_t E_{bought,t} \cdot Price_t - E_{sell,t} \cdot \frac{Price_t}{3}\right) \tag{1}$$

where $E_{bought,t}$ and $E_{sell,t}$ represent the energy purchased and sold to the grid at instant t, and it is assumed that the sale of energy to the grid is remunerated at one third of the purchase price.

While this strategy is the simplest to implement, it is assumed to be the least economically efficient. Without a mechanism to shift consumption to lower-cost periods, it incurs high costs at times of high demand.

B. Rule-based strategy

To improve the efficiency of energy use, a rule-based strategy is introduced to manage storage in a structured manner. In this case, batteries are charged and discharged following predefined criteria, mainly based on the price of electricity and the SoC.

The logic of this strategy is based on two fundamental principles. First, during the 10 hours with the lowest electricity prices, the batteries are charged to take advantage of lower-cost energy. If there is surplus renewable generation, this energy is also stored instead of being fed into the grid. Second, during the 10 hours with the highest electricity prices, the batteries are discharged to supply energy to the system and reduce the purchase of electricity, optimizing cost savings.

To avoid accelerated degradation, restrictions are imposed on SoC levels, keeping it within a safe range between 10% and 90%. In addition, a limit is set on the amount of energy that can be drawn daily from the batteries, adjusted according to their SoH. These rules make it possible to improve system efficiency without the need for complex calculations at every instant of time.

Despite its advantages, the rule-based strategy has some limitations. By following predefined criteria, it may not always guarantee the best possible solution in terms of energy cost. In some cases, the battery may be charged or discharged at non-optimal times, which reduces the savings potential. In addition, this strategy does not consider future degradation of the battery, which could lead to inefficient use in the long term.

C. Optimization-based strategy

To improve the efficiency of energy management, a strategy based on mathematical optimization is implemented, which aims to minimize the energy cost while meeting the operational constraints of the system.

The optimization problem is formulated with the objective of minimizing the total cost of electricity over a 24-hour period, considering the hourly price of electricity, the expected consumption and the available renewable generation. Decision variables include the charging and discharging power of each battery at each hour of the day.

To ensure safe and efficient operation, the problem is subject to multiple constraints: the state of charge of each battery must be kept within the allowed limits; the charge and discharge power must not exceed the maximum capacity of each battery; a daily limit of drawn energy, dynamically adjusted according to the degradation of the battery, must be respected; and the net energy drawn from the grid must comply with the capacity constraints of the system.

The problem is solved using an optimization algorithm based on the Sequential Least Squares Programming (SLSQP) method. This method is widely used in non-linear optimization problems with constraints, as it allows to handle equality and inequality constraints in an efficient way [10].

This strategy is expected to offer several advantages over rule-based management, including reduced energy costs, as the optimized charging and discharging of batteries minimize energy purchases during expensive periods. Additionally, it ensures better battery utilization by avoiding unnecessary cycling that accelerates degradation, thereby extending the lifetime of the storage system. Moreover, the optimization-based approach provides greater flexibility adapting to variations in consumption profiles, renewable generation, and electricity prices to maximize efficiency under changing conditions.

However, its main disadvantage is the higher computational cost compared to the rule-based strategy, even if this cost can be affordable in systems where energy planning is done well in advance.

III. RUL ESTIMATION AND SOH CALCULATION

Battery aging is a determining factor in the performance and cost-effectiveness of the energy storage system. To address this problem, two complementary algorithms are implemented: SoH estimation, which assesses the cumulative degradation of each battery as a function of its use, and RUL prediction, which provides a projection of the time remaining until the battery reaches its End of Life (EOL).

Both calculations are fundamental to optimizing battery management, as they allow for the dynamic adaptation of battery usage to maximize energy storage efficiency and extend their lifetime. In real-world applications SoH is typically provided by the BMS, which continuously monitors the battery's condition. However, in this work, an additional SoH estimation algorithm has been implemented to accurately simulate battery behavior over its entire lifespan. SoH estimation.

The calculation of the state of health of batteries is based on a degradation model that incorporates multiple operational factors that affect their aging. The degradation of a battery is not a linear process, but depends on various conditions of use, such as the charging and discharging current, the temperature at which it operates, and the depth of the cycles performed. In this work, the estimation of SoH is obtained by means of an empirical model that takes these factors into account and adjusts the degradation rate according to their cumulative impact.

The implemented model is based on the relationship between the current capacity of the battery and its initial nominal capacity, adapting the equation from [11]. From measurements of current, temperature and accumulated cycles, the SoH is updated using the equation:

$$\Delta SoH = \beta \cdot \exp(k_T \cdot \frac{T-T_0}{T} + k_{C_{ch}} \cdot C_{\text{cha}} + k_{C_{dch}} \cdot C_{\text{dch}}) \cdot (FEC^{\alpha} - FEC_{\text{prev}}^{\alpha}) \quad (2)$$

where parameters β, k_T, $k_{C_{ch}}$ and $k_{C_{dch}}$ are empirically adjusted to represent the impact of each variable on battery degradation. C_{cha} and C_{dch} represent the effective charge and discharge rates, while *FEC* is the number of cumulative effective cycles. The reference temperature T_0 is set to 293.15 K (equivalent to 20°C), thus allowing the thermal effects on degradation to be modeled.

Over time, this model allows the SoH of each battery to be dynamically adjusted according to its actual usage. This calculation is essential for the energy management strategy, as it allows the implementation of adaptive operating limits that reduce the workload on batteries with higher degradation level.

A. RUL estimation

While the SoH provides an assessment of the current state of the battery, the RUL prediction allows anticipating its future evolution and making long-term strategic decisions. For this purpose, a model based on Gaussian Process (GP) has been implemented, a machine learning technique that allows modeling non-linear relationships and capturing uncertainty in the prediction. The model implemented in the current paper was presented in [12,13].

The RUL estimation algorithm is divided into three main functions. First, data ingestion and preprocessing are performed, where historical records of battery operation are collected, including power used, operating temperature and number of accumulated cycles. During this stage, data filtering is performed to eliminate outliers and interpolation techniques are applied to correct possible absences in the data. In addition, derived variables are generated to facilitate model training, such as energy throughput and the degradation rate observed in previous cycles.

The second function is the training phase of the RUL model. In this work, the GP model is initially trained with historical data from batteries that have experienced different usage profiles, which improves its generalizability. Since the model is trained with a large database, it is not necessary to recalibrate it continuously, but rather a retraining scheme is chosen every three years, incorporating new data obtained during actual system operation (and processed in the previous step). During this phase, the hyperparameters of the model are adjusted to optimize its accuracy, ensuring that the predictions are consistent with the degradation observed in the monitored batteries.

Finally, in the RUL estimation phase, the trained model is run every six months to update the remaining life prediction of each battery. Using the most recent SoH data and operating conditions, the GP extrapolates the expected evolution of the state of health over time, allowing to calculate the number of cycles or the remaining time period before reaching the EOL. Unlike deterministic models, the advantage of the GP-based approach is that it provides a confidence interval, allowing to quantify the uncertainty in the prediction and adapt the energy management strategy accordingly.

B. Dynamic adjustment of operating limits

The estimated SoH and RUL values allow the implementation of dynamic adjustments in the operation for both batteries, the high-power battery and the high-energy battery. If the RUL model predicts that a battery will reach its end of life in a shorter period than expected, the charge and discharge energy limits will be modified to reduce the degradation rate and extend its functionality. Similarly, if a battery's SoH is observed to fall below a critical threshold, power flows can be redistributed to the less degraded battery, maximizing overall system efficiency.

These adjustments extend the lifetime of the energy storage and reduce operating costs by avoiding premature battery replacement. By integrating both strategies into the energy management system, both short- and long-term optimization is guaranteed, ensuring a balance between cost-effectiveness and sustainability of energy storage.

IV. RESULTS

To evaluate the effectiveness of the proposed optimized EMS, the different algorithms have been combined in a long-term simulation, replicating a realistic operating scenario over a ten-year period. The objective of this simulation is not only to analyze the energy cost reduction obtained with each strategy, but also to ensure that the batteries do not reach their EOL before the end of the analysis period.

The results show significant differences in terms of operating costs between the different strategies. In the case where no batteries are used, the total operating cost amounts to €68,200 over ten years, reflecting the complete dependence on the grid to meet the demand. The rule-based strategy reduces this cost to €65,400 by allowing the batteries to store energy at times of low price and use it at times of higher cost. However, the largest reduction is obtained with the optimization strategy, where the final cost drops to €51,800, which represents a 24% saving compared to the scenario without storage and 21% compared to the rule-based strategy. It is important to note that these calculations do not take into account the cost of the batteries themselves.

These results are reflected in Figure 1, which illustrates the cumulative cost difference over the ten years for each strategy. The graph highlights how the use of batteries reduces grid dependence and optimizes energy flows, with the optimized approach achieving the greatest cost reduction.

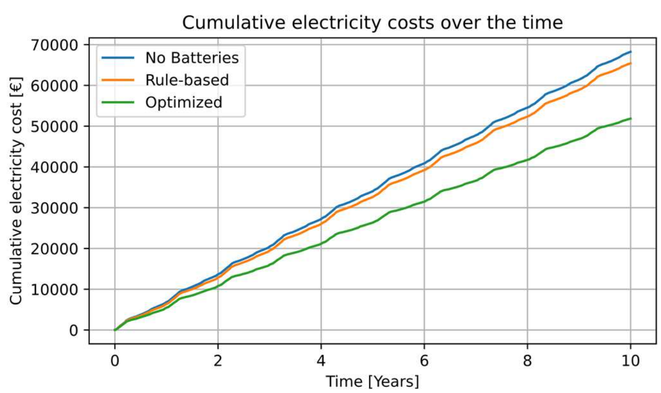

Figure 1. Cumulative cost of the different strategies.

Beyond the economic impact, the optimization strategy also introduces a key difference in the way batteries are used. While both the rule-based and optimized strategies dynamically adapt the operational limits of the batteries based on their SoH and RUL, their behavior differs significantly. As depicted in Figure 2, the rule-based strategy, the energy limits are progressively reduced over time to ensure that the battery lifespan meets the predefined requirements. However, this strategy makes full use of the allowed energy every day, meaning that the battery operates at the maximum permitted charge and discharge limits, regardless of whether it is the most cost-effective choice.

In contrast, the optimized strategy shows a more dynamic behavior, as shown in Figure 2, where the allowed energy fluctuates in the early years. Unlike the rule-based strategy, where the energy limit strictly decreases, in the optimized case the allowed load and discharge levels vary over time, in response to economic and operating conditions. During the early years of operation, the optimizer adjusts these limits dynamically, sometimes allowing greater energy efficiency and sometimes restricting usage to minimize unnecessary cycling. However, in the later years, it can be observed how the optimizer does not always use the maximum allowed energy and thus the battery experiences less degradation compared to the rule-based approach. As a result, at the end of the simulation, the battery retains a better SoH, allowing it to withstand higher charge and discharge levels than the rule-based battery.

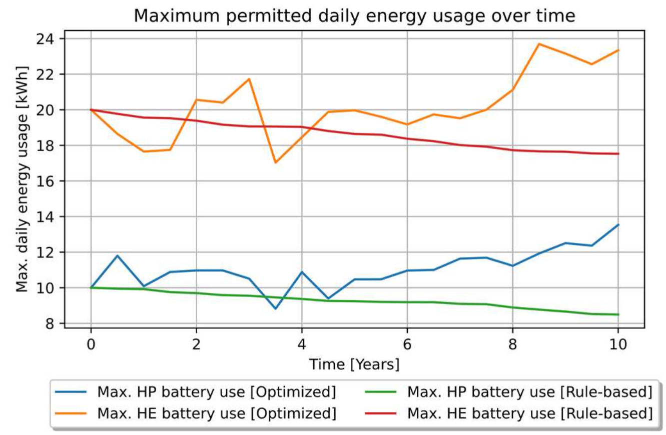

Figure 2. Maximum permitted daily energy usage for each battery over time.

Another important observation from Figure 2 is that the actual battery usage in the optimized strategy often, on numerous occasions, remains below the imposed limits. This highlights a fundamental advantage of the optimization approach, since instead of imposing the total energy usage available each day, the optimizer selectively decides when it is economically beneficial to charge or discharge.

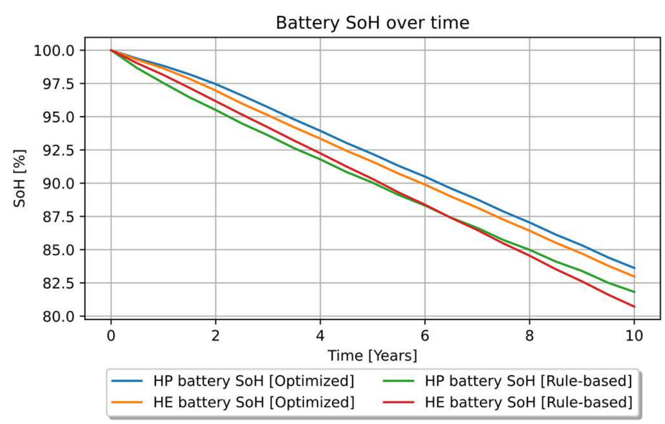

Figure 3. SoH of each battery over time.

Finally, Figure 3 presents the evolution of the SoH of both batteries (HP and HE) over the ten years of operation for the two cases. In this graph, it can be seen how the degradation is kept under control thanks to the implementation of the RUL algorithm, which dynamically adjusts the allowed use of the batteries. As a result, at the end of the simulation period, both batteries retain a SoH above 80%, indicating that they can continue to operate without immediate replacement. This result is particularly relevant, as it demonstrates that intelligent storage management not only optimizes energy costs, but also prolongs the lifetime of the system, avoiding additional costs associated with battery replacement.

V. EMS DEPLOYMENT IN A CLOUD-EDGE BASED PLATFORM

Once the complete EMS has been developed and validated in a computer simulation framework, the optimization-based EMS has been deployed in a Cloud-Edge based platform, enabling the industrialization of the complete solution, and acting over real storage systems and inverters.

To do so, some blocks of the EMS have been uploaded to the Cloud, taking advantage of its computational capabilities, and other blocks of the EMS have been deployed into an Edge device, locating this device together with the storage systems and inverters, and communicating continuously to them, as presented in Figure 4.

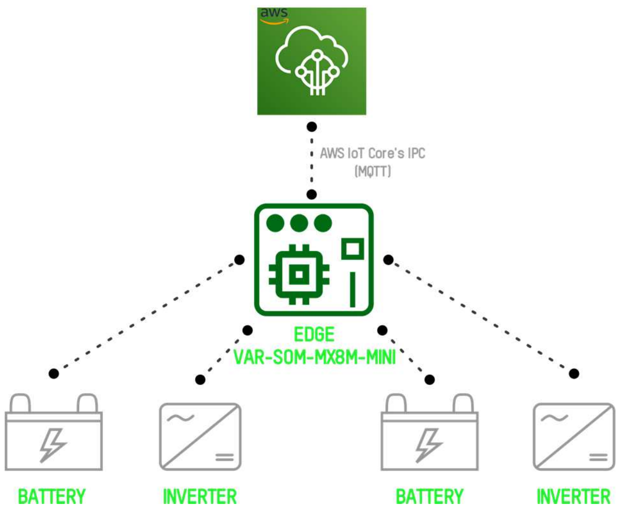

Figure 4. Cloud-Edge platform diagram.

Going into detail, and explaining the development deployed in the Cloud, the following Figure 5. shows internal blocks used in the Cloud environment.

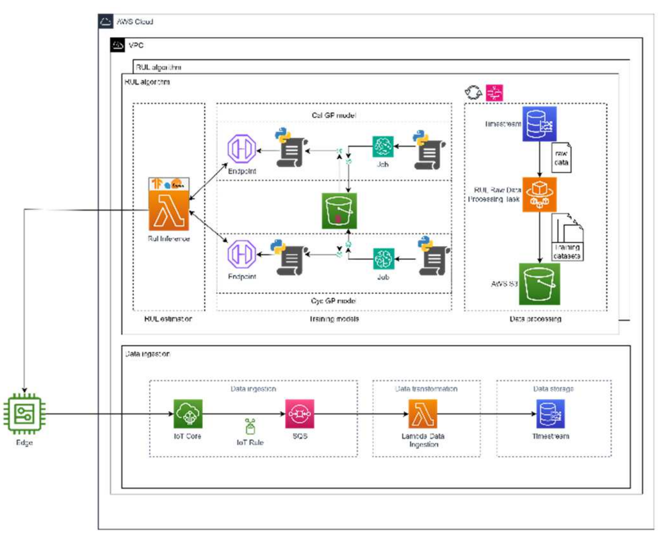

Figure 5. Cloud architecture for complete RUL lifecycle process.

The Cloud workload is separated in two steps. On the one hand, the data ingestion process is developed and on the other hand the RUL algorithm is executed twice, one for each battery. Therefore, in the data ingestion process, the data has been uploaded from the Edge device, and after data ingestion and transformation, the data is stored in a Timestream database. Moreover, in the RUL algorithm execution, the data is loaded from the previously mentioned Timestream, it is processed, and Gaussian Processes models are trained and deployed. Afterwards, by a Lambda, the RUL estimation is calculated. This process is executed twice, one for each battery. These RUL estimations, are, afterwards, send to the Edge device, where the EMS algorithm uses them for controlling both storage systems.

Once the results of the RUL algorithm have been received in the Edge, the same process mentioned above is followed, where the maximum daily energy that each of the batteries can provide is adjusted in order to meet the life target previously set.

VI. CONCLUSIONS

This work has presented an EMS designed to optimize the use of storage in a residential building with solar photovoltaic generation. Three energy management strategies have been evaluated and a degradation model has been integrated to dynamically adjust the operational limits of the batteries and extend their lifetime.

The results obtained in a simulation of ten years of operation have shown that the use of batteries allows a significant reduction in energy costs, especially when an optimization strategy is employed. Compared to the scenario without storage, the rule-based strategy was able to reduce the total cost by 4%, while the optimized strategy achieved savings of 24%, demonstrating the importance of advanced planning in energy management.

In addition, thanks to the integration of the RUL model, it was possible to adapt the charge and discharge limits over time, avoiding accelerated aging. As a result, at the end of the simulations, both batteries retained a SoH above 80%, suggesting that they can continue to operate without immediate replacement.

On the other hand, it was observed that optimization-based EMS does not always bring batteries to their limit, but modulates their use based on energy cost-effectiveness and system health status. This demonstrates that optimization-based control can efficiently balance cost reduction with battery preservation, maximizing the return on investment of energy storage.

Finally, implementing EMS on a Cloud-Edge computing-based platform offers additional advantages in terms of scalability and real-time processing capability.

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