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RESEARCH ARTICLE

Development and Comparison of Rule- and Machine Learning-Based EMS for HESS Providing Grid Services

HAKAN POLAT[1,2], (Member, IEEE), ENEKO UNAMUNO[3], (Member, IEEE), DAVID CABEZUELO[3], (Member, IEEE), THOMAS GEURY[1,2], (Member, IEEE), AND OMAR HEGAZY[1,2], (Senior Member, IEEE)

[1]MOBI-EPOWERS Research Group, ETEC Department, Vrije Universiteit Brussel, 1050 Brussels, Belgium
[2]Flanders Make, 3001 Heverlee, Belgium
[3]Electronics and Computing Department, Mondragon Unibertsitatea, 20500 Arrasate-Mondragón, Spain

Corresponding author: Omar Hegazy (omar.hegazy@vub.be)

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ABSTRACT In this paper, a smart machine-learning-based energy management system (MLBEMS) is developed for a hybrid energy storage system (HESS). This HBESS consists of batteries with high-energy (HE) and high-power (HP) characteristics, to provide grid-supporting services. The aim of the MLBEMS is to improve the overall battery lifetime and achieve state-of-charge (SoC) balancing for two different use cases (UC). UC1 involves enhanced frequency regulation for the Pan-European grid, while UC2 pertains to an electric vehicle (EV) charging station with photovoltaic (PV) generation. The designed MLBEMS is compared with a rule-based energy management system (RBEMS) from the literature with similar use cases. To ensure optimal power sharing between the battery modules, an optimization model is created using real battery aging data. Using a genetic algorithm, optimal power sharing is achieved for various initial SoC conditions. The generated dataset is subsequently utilized to train a machine-learning regression model, and the resulting prediction function is imported into MATLAB/Simulink. In UC1, MLBEMS achieved a 39.3% better SoC balancing compared to RBEMS, along with 36.5% and 22.6% higher battery lifetimes for HE and HP batteries, respectively. Similarly, for UC2, MLBEMS achieved a 68.5% improvement in SoC balancing, along with 53.6% and 45.8% higher battery lifetimes for HE and HP batteries, respectively.

INDEX TERMS Energy management system, hybrid energy storage system, machine learning, stationary storage system.

I. INTRODUCTION

The environmental concerns, increasing fossil fuel prices, and the reduction in operational and capital costs of renewable energy sources (RES), among other factors, are driving the accelerated electrification of the energy sector. This trend provides significant incentives for electrical mobility and the massive installation of RES [1]. However, the dependency on weather conditions causes RES to be highly variable in terms of power generation [2]. This variability, coupled with an insufficient amount of energy storage in the energy system, necessitates a delicate balance between supplied and demanded power to avoid generation curtailments and consequent economic losses.

Another challenge emerging in this transition is the replacement of conventional power plants, primarily coal/gas plants, which connect to the grid via synchronous generators with high mechanical inertia, by converter-interfaced RES. These converter-interfaced RES do not inherently respond under power perturbations, leading to higher frequency swings that can jeopardize the system stability, especially when the penetration of RES in the system is high [3].

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Consequently, research on power quality and grid stability has significantly increased in recent years.

In this context, converter-based energy storage systems (ESS) are expected to play a key role in the operation of the system, since they increase the flexibility to manage the generated and demanded power. ESSs can be used in a variety of applications ranging from frequency regulation to electric vehicle (EV) charger power and ramp-rate limit, uninterruptible power supplies (UPS), backup energy, storage of excess renewable energy generation, etc. In the literature, there are different ESS technologies (battery, flywheel, hydrogen, super-capacitors, pumped hydro, thermal,...) [4], [5], [6]. With the increased demand for EV batteries, the mass production, and research on electrochemical storage unit has also increased. Therefore, the cost of battery energy storage systems (BESS) has decreased and this has become a profitable sector [7].

Compared to single BESSs, Hybrid BESSs (HBESS) increase the degrees of freedom to provide a wide range of grid services while decreasing the degradation of the system [8]. The idea is to combine two or more battery chemistries with different energy and power ratings. By optimally using their characteristics, for example allocating the faster power setpoints to the high-power (HP) and the slower setpoint to the high-energy (HE) battery technology, the overall lifetime of the system can be increased [9], [10], [11], [12]. Moreover, the lower internal resistance of HP batteries makes it possible to reduce the size of the system [9], [10], [11]. Therefore, optimizing the size/cost/lifetime of the HBESS results in a superior system compared to a single-chemistry BESS [9], [10], [11], [13]. The general structure of a HESS with two battery technologies is represented in Fig. 1. Parameters of the batteries and the grid is presented briefly in Table 1. The details of the power electronics are not presented due to confidentiality. However, they consist of two-stage solutions with a DC/DC conversion stage followed by a grid-tied bi-directional inverter. More details of the battery and power electronics and the system sizing can be found in [13].

TABLE 1. Battery and grid parameters.

Parameter	Value
HE battery Capacity	50 kWh
HE battery Chemistry	Lithium Iron Phosphate (LFP)
HP battery Capacity	50 kWh
HP battery Chemistry	Lithium Nickel Manganese cobalt oxide (NMC)
Grid voltage	400 V_{l-l}
Grid frequency	50 Hz

Even though a HESS can be more performant compared to a BESS, its advantages can be maximized only with a well-designed energy management system (EMS). Compared to single-technology ESSs, in hybrid systems the EMS has to calculate not only the power setpoint to provide a certain grid service, but also to optimally allocate the power internally between the different battery to improve the system performance and maximize its lifetime. In the literature, the EMS solutions for HESSs can be classified in two groups, namely smart and classical EMSs [14]. Classical EMS structures use equation-, droop- and/or filter-based mathematical approaches. In [15], different rule-based EMS for grid connected BESS is presented namely frequency based inertia control and swing-equation based inertial control. In [16], different equation based control methods are presented for improved voltage stability in micro-grids including RESs and HESSs. In [17], a review for HESS control for microgrids is presented where different methods like fuzzy-logic [18], filter-based [19] or model predictive control [20] are presented. In [21], an intelligent fuzzy logic is presented to distribute the total power demand among a fuel-cell, battery and solar panels. The demand profile is created using a mission profile created for an EV. The proposed algorithm is also tested in real time for a scaled-down system. Smart EMS structures, on the other hand, employ methods such as online optimization or machine-learning (ML) algorithms. In [22], the degration model of the system is improved and with the use of Markovian degradation model coupled with reinforced learning a cost saving of 5-29% is achieved. In [23], a dynamic power management for DC microgrid with HESS is presented. In the article Hybrid Bat Search and ANN is used. The ANN model is found superior to conventional method in terms of voltage overshoot and settling time for different cases. In [24], a HESS with battery/ultra-capacitor system is optimized using neural networks. The proposed neural network strategy is found to increase the battery life over 60% compared to a conventional rule-based method. Since smart EMS methods derive from either complex, realistic data-driven digital twin models or actual system operational data, they are superior to classical approaches [25]. However, since the EMS is designed for a specific system, up-scaling or multi-purposing the developed algorithm is a challenging task.

The aim of this paper is to compare the improved interoperable rule-based EMS (RBEMS) developed in [26], to machine learning-based EMS (MLBEMS). MLBEMS

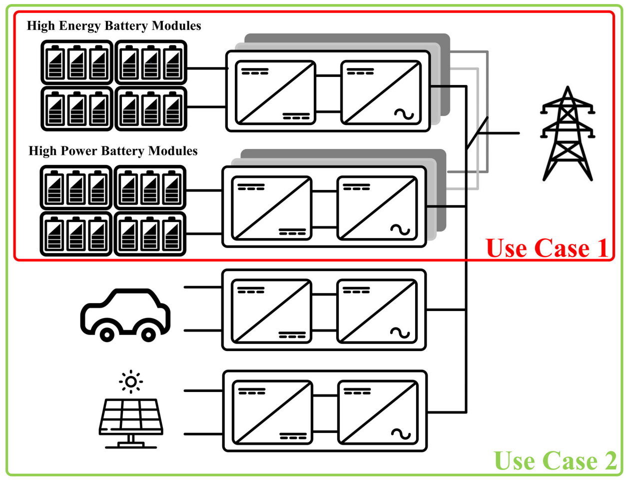


FIGURE 1. Diagram of a HESS system including the power electronics.

aims to include the consumed life of the batteries and provide a power-sharing such that the overall system lifetime is improved and hence the operational costs are reduced.

The paper organization is as follows. In II, two different grid services are introduced, which will be used to compare the performance of the proposed EMS over more conventional approaches. These use cases consist of an enhanced frequency response service, and a peak power and ramp-rate limited EV charger station. In III, the framework of the MLBEMS will be presented. During the ML optimization, SoC balancing and the battery lifetime are chosen goals. Finally in V and VI, the RBEMS and MLBEMS results are presented, compared and discussed.

II. USE CASE DESCRIPTIONS

Grid-connected BESSs can be employed to provide a wide range of various services like frequency regulation, RES excess energy storage, improved power quality applications, …Most of these systems, however, are specifically designed for a single application, and their adaptation to other use cases is often unfeasible.

The aim of the EMS proposed in this paper is to be interoperable, meaning that with slight modifications in the control parameters, it might be used for the provision of different grid services.

In this section two relatively different use cases are described. They will be used in subsequent sections to compare the performance of the proposed MLBEMS versus an updated version of the RBEMS proposed in [26]. These use cases represent the Pan-European grid scenario and an EV charging station with PV generation. In the following sections a brief description of these use cases is provided.

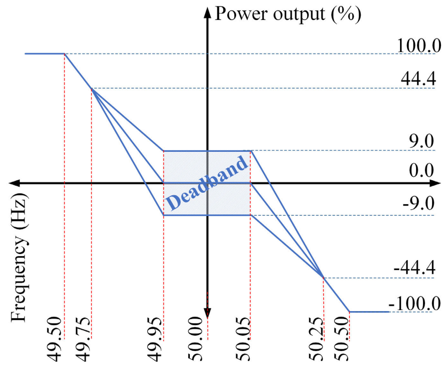
A. USE CASE 1: PAN-EUROPEAN GRID

In the first use case (UC1), the HESS is integrated into the Pan-European power grid to participate in the frequency support. The primary goal is to deliver a frequency regulation service known as Enhanced Frequency Response (EFR). The EFR service, developed within the regulatory framework of the UK market, plays a crucial role in supporting the smooth integration of RES into the grid. For a comprehensive understanding of this service, the reader can refer to [27]. In essence, this service involves the dynamic exchange of power between the HESS and the grid, responding to the specific frequency conditions at the point of interconnection. This mechanism aids in the efficient regulation of frequency, ensuring the reliable operation of the grid while accommodating the variability of RESs.

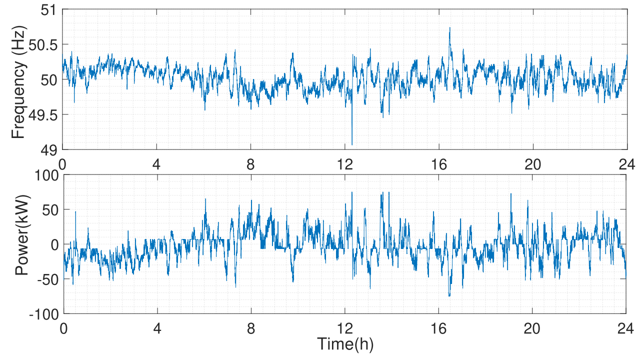
Using a standard frequency support algorithm presented in [26], the power demand from the HESS is given in Fig. 2.

B. USE CASE 2: EV CHARGING STATION

In Use case 2 (UC2), the HESS runs in parallel to a high-power EV charging station. As distribution grids are challenged by the widespread integration of these stations, many aspects of the existing infrastructure struggle to accommodate additional high-power consumers without the need for oversized transmission and distribution lines and transformers. In this context, the HESS serves a dual purpose within this application.



(a) EFR Power vs. Frequency graph.



(b) Grid frequency and power demand for an entire day.

FIGURE 2. (a) EFR power vs. frequency. The power demand from the HESS is determined by the deviation from the nominal grid frequency. (b) The grid frequency and power demand from HESS for an entire day.

Firstly, it aims to limit the maximum power absorbed by the EV charging station. By regulating the power, the HESS ensures that the charging station operates within predefined bounds, preventing excessive strain on the distribution grid. This limitation aids in deferring the investments in new distribution grid infrastructure.

Secondly, the HESS plays a critical role in managing the rate at which power is exchanged by the charging station. By restricting the rate of power, sudden fluctuations that could disturb the overall operation of the grid are prevented. This controlled ramping ensures a smoother integration of the EV charging station into the distribution grid, minimizing grid disturbances and maintaining a reliable and stable electricity supply.

The power demand of the EV charging station (P_{EV}) is presented in Fig. 3. In this case, the power consumed from the grid is limited to 120 kW, and its maximum rate is defined as 100 W/s. In order to limit these values, the HESS has to exchange the power represented in blue (P_{HESS}).

III. MACHINE LEARNING-BASED EMS

The framework of the MLBEMS development is presented in Fig. 4. Initially, the charge loss aging models of both battery chemistries are obtained using accelerated battery

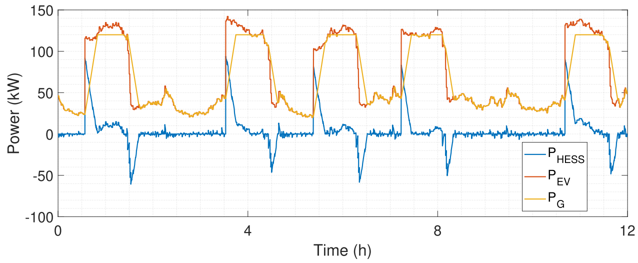


FIGURE 3. Mission profile for the UC2. P_{EV} is the demand of EV station, P_{HESS} is the power demanded by the HESS, P_G is the power demand from the utility grid. The peak power is limited to 120 kW and the ramp rate is limited to 100 W/s.

aging testing. The details of the aging maps will be presented in subsection III-A. To create the dataset, a multi-objective genetic algorithm is used. The input of the optimization is the total power demand from the grid (P_{grid}), the state of charge (SoC) of the batteries, the battery aging maps, and some constants of the HESS system such as the charge loss of the batteries from the beginning of life (Q_{loss}), the battery voltages and capacities, etc. For many combinations of power demand, SoC and Q_{loss}, a solution space is generated. For all initial conditions, the optimization is repeated and the dataset is created.

A. BATTERY CHARGE LOSS MODEL

In the MLBEMS, the aim is to improve the overall battery lifetime, decrease operational costs, and extend the overall system lifetime. Therefore it is crucial to estimate the charge loss for a certain C-rate and time duration for all conditions. Both the HE and HP batteries are put into accelerated aging chambers and the semi-empirical aging models are obtained using Sigma-Point Kalman filter as presented in [28]. The lifetime model used in the optimization framework is as follows:

The state of Health (SoH) of a battery is presented in (1).

$$SoH(\%) = \frac{100}{CC}(CC - Q_{loss}) \tag{1}$$

where Q_{loss} is the charge loss from the beginning of life and CC is the total capacity of the batteries. The change in Q_{loss} can be expressed as (2).

$$\frac{\partial Q_{loss}}{\partial t} = \frac{\partial Q_{cyc,loss}}{\partial t} + \frac{\partial Q_{cal,loss}}{\partial t} \tag{2}$$

where $Q_{cyc,loss}$ and $Q_{cal,loss}$ are cycle and calendar charge losses. $\frac{\partial Q_{cyc,loss}}{\partial t}$ is a 4-D look-up-table (LUT) whose axis are Q_{loss}, temperature (T), state of charge (SoC) and C_{rate}. Similarly, $\frac{\partial Q_{cal,loss}}{\partial t}$ is a 3-D LUT depending on Q_{loss}, temperature (T) and state of charge (SoC).

During the optimization the $\frac{\partial Q_{cyc,loss}}{\partial t}$ is calculated for a short duration. Therefore the C-rate, SoC, temperature and Q_{loss} are assumed to be constant, and (2) can be discretized as follows:

$$\frac{\Delta Q_{loss}}{\Delta t} = \frac{\Delta Q_{cyc,loss}}{\Delta t} + \frac{\Delta Q_{cal,loss}}{\Delta t} \tag{3}$$

B. OPTIMIZATION MODEL

The optimization is selected as genetic algorithm (RCGA). This method is selected due to non-linearities and its performance of finding the global optimum in the solution space. Some parameters of the RCGA are given in Table 2. The parameters were adjusted by checking the convergence of the RCGA using different optimization test functions [29].

TABLE 2. Parameters of the RCGA method.

Parameter	Value
Number of Population	500
Number of Generation	25
Number of Output	2 (P_{HP}, P_{HE})
Higher and Lower Boundaries of P_{HP}, P_{HE}	$\pm 75\ kW$
Crossover rate	80%
Number of mutation	20%
Mutation rate	20%
Crossover method	Tournament selection
Number of elites	2

The cost function consists of 3 different elements which are SoC balancing, battery aging, and the power supplied to the grid. The SoC balancing and battery aging are combined into a single cost function by using weighting factors denoted as ω. The power demand from the grid has to be satisfied at all conditions and is therefore implemented as a higher/lower boundary penalty condition. The optimization function is formulated as follows:

$$\begin{aligned} &min \quad X = \omega_1 SoC_{Bal} + \omega_2 BAT_{LT} - Q_{penalty} P_{error} \\ &subject \quad to \\ &\qquad \omega_1 + \omega_2 = 1 \\ &\qquad P_{error} = |P_{HP} + P_{HE} - P_{demand}| \\ &\qquad Q_{penalty} = 0 \quad if \quad P_{error} < P_{error,max} \\ &\qquad Q_{penalty} = 100 \quad if \quad P_{error} \geq P_{error,max} \end{aligned} \tag{4}$$

1) SoC BALANCING

The SoC balancing is crucial to extend the operation duration of the HESS. When the SoC of one of the batteries reaches the higher or lower boundary the operation has to be stopped, or the power should be allocated such that it is far from optimal for the battery lifetime. However, limiting the SoC difference may also result in non-optimal power sharing for battery lifetime. Therefore, it is important to have control over the SoC difference to find the optimal balance between system operation extension and battery lifetime reduction. The SoC balancing equation can be expressed as:

$$\begin{aligned} &SoC_{Bal} \\ &\quad = k_1 P_1 P_2 P_3 + k_2 P_4 \\ &P_1 = \frac{|SoC_{HE} - SoC_{HP}|}{60} \\ &P_2 = sign(|SoC_{HE} - SoC_{HP}| - |SoC_{HE,Final} - SoC_{HP,Final}|) \\ &P_3 = \frac{|SoC_{HE} - SoC_{HE,Final}| + |SoC_{HP} - SoC_{HP,Final}|}{|SoC_{HE} - SoC_{HE,Best}| + |SoC_{HP} - SoC_{HP,Best}|} \\ &P_4 = \frac{|SoC_{HE} - SoC_{set}|}{SoC_{set}} + \frac{|SoC_{HP} - SoC_{set}|}{SoC_{set}} \end{aligned} \tag{5}$$

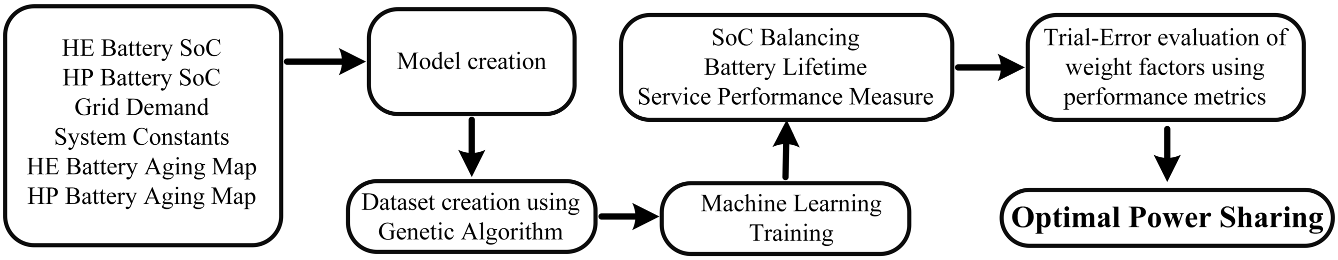


FIGURE 4. The framework and steps for the MLBEMS strategy. The model is trained using GA. Later the dataset is trained with regression learner and the cost function is tuned for optimal SoC balancing, battery lifetime and service performance measure.

The SoC_{Bal} has 4 parts. The first part denoted as P_1, is a term that minimizes the effect of SoC balancing as the SoC's are close to each other. When the SoC's are already balanced, it is better to allocate power such that it maximizes the battery lifetime. The second term denoted as P_2, shows whether the initial SoC difference is more or less than final case. The term is positive if the final SoC difference is smaller than the initial condition. The third term denoted as P_3 indicates how well the SoC balancing is achieved compared to the best case ($SoC_{HP,best}$, $SoC_{HE,best}$). The best case is when both HE and HP batteries are charged/discharged with maximum power such that their SoCs are closer to each other. During the operation, no constraint is put on providing the demanded power. Therefore, it can be seen as the most amount of SoC balancing that can be achieved for a certain timeframe. Finally, the last term P_4 tries to bring both SoCs to the setpoint. This setpoint is UC-specific. As an example, while it might be interesting to keep this term around 50% for providing the EFR service (UC1), it is more interesting to bring the SoC to the highest boundary (e.g. 80%) for limiting the power in an EV charging station (UC2). In UC1, the variation of the frequency is unknown. Therefore, it is unknown whether the system will have to supply or absorb power from the grid. Hence, it is best to keep it at 50% such that the operation is extended as long as possible. In UC2, it is known that the moment an EV is connected, the HESS will have to supply power to the grid. Therefore, it is best to keep it fully charged such that the service in this case can be provided to as many EV charging cycles as possible. The terms k_1 and 4 k_2 are internal weighting factors whose summation is equal to unity. A simplified illustration of the SoC balancing can be seen in Fig. 5.

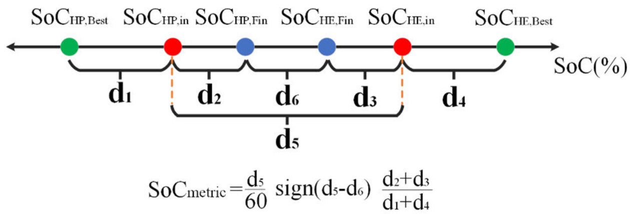


FIGURE 5. Visual illustration of SoC balancing metric.

2) BATTERY LIFETIME

The battery lifetime is separately calculated, using the discrete form presented in section III-A. For each finite step, the charge loss for HP and HE batteries denoted as $\Delta Q_{loss,HP}$ and $\Delta Q_{loss,HE}$ is estimated using the LUT. Then the cost function is written as in (6).

$$BAT_{LT} = 1 - \alpha_1 \frac{|\Delta Q_{loss,HP} - 3.33\Delta Q_{loss,HE}|}{|\Delta Q_{loss,HP} + 3.33\Delta Q_{loss,HE}} - \alpha_2 \frac{\Delta Q_{loss,HE} + \Delta Q_{loss,HP}}{\Delta Q_{loss,HE,max} + \Delta Q_{loss,HE,max}} \qquad (6)$$

where α_1 and α_2 are internal weighting factors whose summation equals to one. α_1 represents the weight of the term of equating the HP battery charge loss to 3.33 times the HE battery module. This factor is derived from the maximum full cycle of the NMC and LFP batteries. The LFP batteries have 3.33 times more cycle life [13]. The second term α_2 is the weight to minimize the total charge loss. While increasing α_1 will result in a battery aging with a ratio of their total cycle life, it does not necessarily imply an overall improved lifetime. Increasing the second term α_2 will result in a minimization of the overall battery aging, but it doesn't imply a controlled battery aging. Therefore, the internal weighting factors should be chosen according to the system requirements.

C. MACHINE LEARNING BASED EMS TRAINING

To train the model to be capable of accurately predicting an optimal power sharing, a wide solution space needs to be covered with a high number of data. Therefore, the initial conditions are varied with small increments, covering the entire solution space. For all elements of the dataset, the optimization model is repeated. The results are later fed into the "Regression Learner" in MATLAB toolbox to find the optimal regression learner method. Moreover, for each UC, different cost function weighting factors and internal weighting factors are tested. Based on the results of these tests, the final set of parameters is selected to reach an adequate compromise between the provision of the grid service, the SoC balancing and the battery degradation. The parameters for UC1 and UC2 are presented in Table 3.

IV. COMPARISON METHODOLOGY

The main advantage of the MLBEMS proposed in this paper, compared to the RBEMS, is that the power setpoints

TABLE 3. Machine learning training parameters. (GIE: gaussian isotropic exponential).

	Use Case 1	Use Case 2
Importance Factors (ω_1, ω_2)	0.8 , 0.2	0.7 , 0.3
SoC_{Bal} factors (k_1, k_2)	0.9 , 0.1	0.9 , 0.1
BAT_{LT} factors (α_1, α_2)	0.2 , 0.8	0.2 , 0.8
SoC_{Set}	50%	80%
Machine Learning Model	GIE	GIE
Basis Function	Constant	Constant
Basis Function	Constant	Constant
Kernel Scale	141.86	141.86
Sigma	$2.2e^{-4}$	$2.2e^{-4}$

are calculated to optimize the battery aging and hence the operational expenditure of the system. The aim in this section is to explain the metrics that have been employed to carry out a detailed comparative evaluation of these two EMSs. In order to compare both methods' performance, it is necessary to define some criteria showing the advantages of one method over the other. In this paper 3 different criteria are defined, namely root mean square error of SoC (SoC_{RMSE}), battery charge loss, and system performance measure (SPM). It must be highlighted that the latter is a metric to determine how well the HESS is providing the EFR service, so it is only applicable to UC1.

A. ROOT MEAN SQUARE ERROR OF SOC

One of the main ideas behind including the SoC balancing into both the original RBEMS and the proposed MLBEMS optimization framework is to increase the HESS's available energy to provide the requested grid services. This will reduce the instances where one of the battery modules reaches the maximum and minimum SoC boundaries, which are 80% and 20%, respectively. The longer the HESS provides the grid service, the higher is the revenue and hence the lower the return of the investment of the system.

The discrete SoC_{RMSE} is calculated for the entire mission profile for both UC1 and UC2 based on the following equation:

$$SoC_{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(SoC_{HP}(i) - SoC_{HE}(i))^2}{n}} \tag{7}$$

In the discrete formulation, n is the total number of data available. $SoC_{HP}(i)$ and $SoC_{HE}(i)$ are the SoC's of the HP and HE batteries at the given time instant, respectively. From (7), it can be concluded that as the value of SoC_{RMSE} is closer to zero, the SoC balancing will be better.

B. BATTERY CHARGE LOSS

The changes in the battery charge loss (ΔQ_{loss}) for both HE and HP batteries are recorded in an array denoted by X for the entire mission profiles, as shown in (8).

$$X = [\Delta Q_{loss,1}, \Delta Q_{loss,2}, \cdots, \Delta Q_{loss,n-1}, \Delta Q_{loss,n}] \tag{8}$$

Then the total charge loss for a single mission profile (Q_{loss}) is calculated by taking the discrete integral of the array X. In (9), t_{step} is the time step between each element of X.

$$Q_{loss} = t_{step} \sum_{i=1}^{n} X_i \tag{9}$$

C. SERVICE PERFORMANCE MEASURE (SPM)

The EFR *p/f* curve has higher and lower boundaries for the power transfer between the grid and HESS. This boundary is higher as the frequency deviation from the nominal value is smaller, and the band gap decreases as the frequency diverges. The SPM is a metric that determines how well the HESS is providing the power requested according to the EFR p/f curve shown in Fig. 2.

The calculation of the SPM is carried out according to (10). Ideally, the SPM is expected to be unity, meaning that the service is constantly provided within boundaries. However, when the SoC boundaries or maximum power constraints are met, the system is not capable of providing the services. Therefore the SPM starts to decrease from 1. P_{norm} is the normalized power transferred to the grid. P_{env} is the normalized power of the envelope in the EFR curve [27]. P_{high} and P_{low} are the higher and lower power limits of the EFR curve, respectively.

$$SPM = \begin{Bmatrix} 1, & \text{if } P_{low} \leq P_{HESS} \leq P_{high} \\ 1 - |P_{norm} - P_{env}|, & \text{if } P_{HESS} \leq P_{low} \\ 1 - |P_{norm} - P_{env}|, & \text{if } P_{high} \leq P_{HESS} \end{Bmatrix} \tag{10}$$

V. RESULTS AND COMPARISON

In this section, the RBEMS and MLBEMS results are presented and compared.

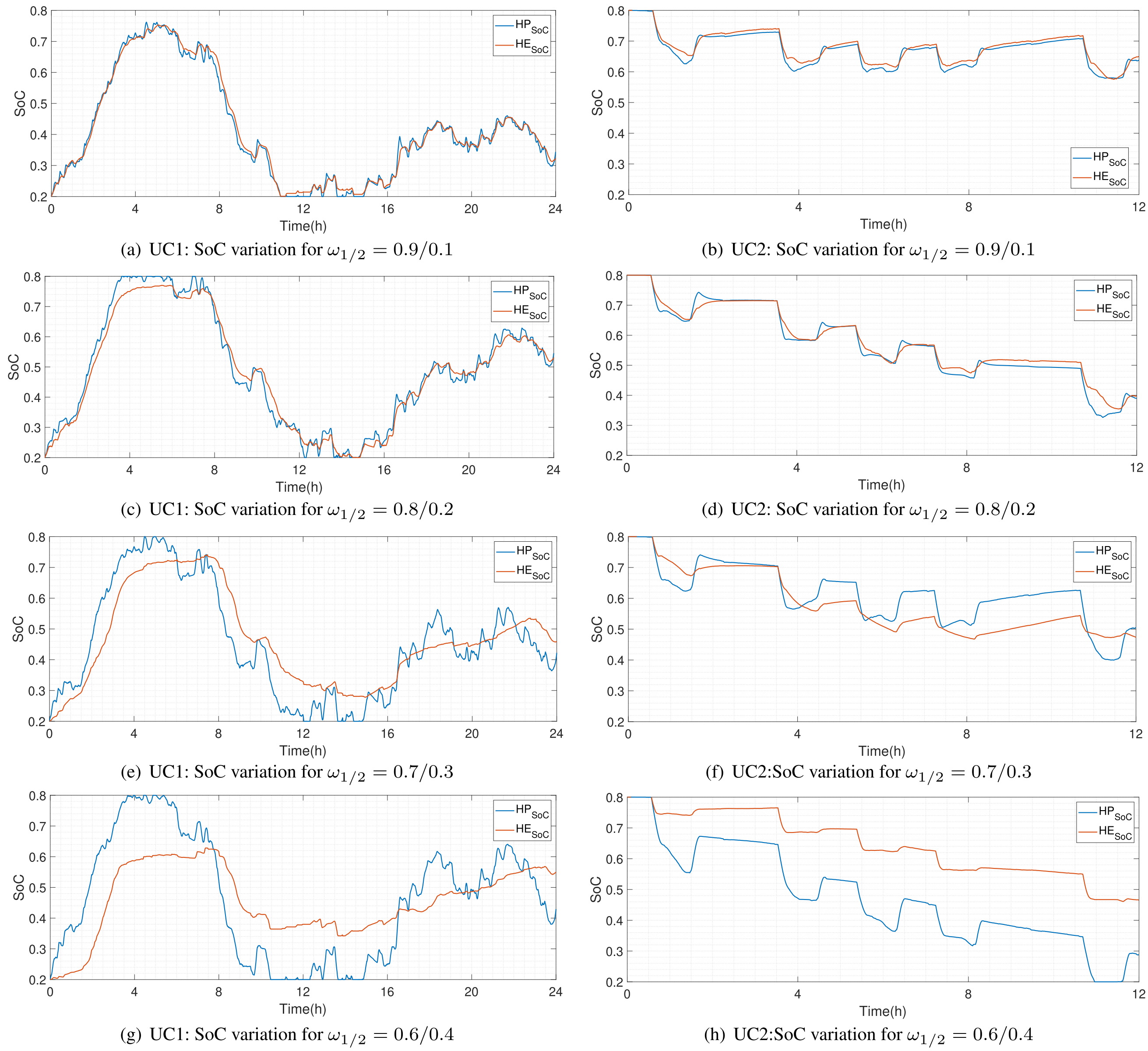
A. EFFECT OF WEIGHTING FACTORS (ω_N) ON THE SOC BALANCING

In section III, the objective was to maximize X where its parts are SoC_{Bal} and BAT_{LT}. The weighting factors are one of the key elements in the optimization determining the performance of the overall MLBEMS. The weighting factor ω_1 is swept from 0.9 to 0.6 with 0.1 decrements. The weighting factor ω_2 is adjusted such that $\omega_1 + \omega_2 = 1$. The results for UC1 and UC2 are presented in Fig. 6.

The SoC_{RMSE}, Q_{loss} and SPM for both use cases are presented in Table 4. For UC1, the weighting factors ω_{1-2} are defined as 0.8 and 0.2, respectively. This parameters are selected since, it shows great compromise between SPM, SoC balancing and battery lifetime. Compared to other weight factor combinations, it is the second best in SPM, second best in SoC balancing, third and second for HE and HP battery lifetime. Similarly for UC2, the weighting factors ω_{1-2} are defined as 0.7 and 0.3, respectively.

B. RESULTS FOR RBEMS AND MLBEMS

In this section, the performance results for RBEMS and MLBEMS are presented for both use cases (see descriptions in section II).



(a) UC1: SoC variation for $\omega_{1/2} = 0.9/0.1$

(b) UC2: SoC variation for $\omega_{1/2} = 0.9/0.1$

(c) UC1: SoC variation for $\omega_{1/2} = 0.8/0.2$

(d) UC2: SoC variation for $\omega_{1/2} = 0.8/0.2$

(e) UC1: SoC variation for $\omega_{1/2} = 0.7/0.3$

(f) UC2:SoC variation for $\omega_{1/2} = 0.7/0.3$

(g) UC1: SoC variation for $\omega_{1/2} = 0.6/0.4$

(h) UC2:SoC variation for $\omega_{1/2} = 0.6/0.4$

FIGURE 6. UC1 and UC2 mission profile SoC variation using MLBEMS for different weighting factor combinations.

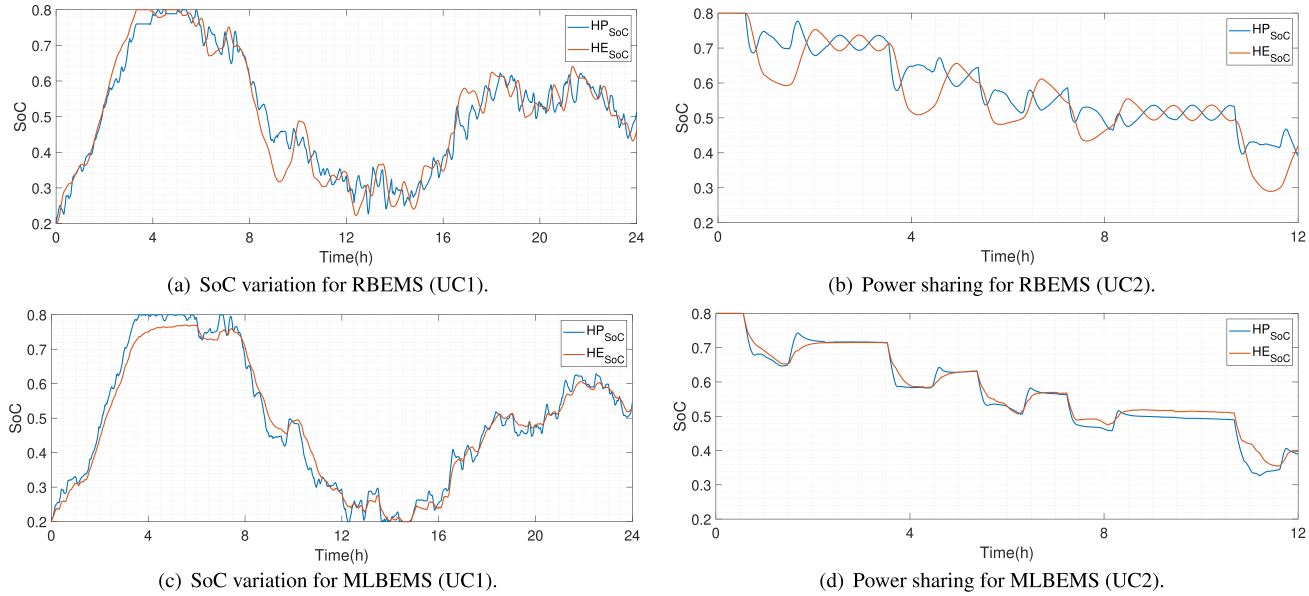
For UC1 and UC2, the system is run for an entire mission profile as presented in Fig. 2 and Fig. 3 using both RBEMS and MLBEMS, respectively. In Fig. 7, the power sharing between the HE and HP modules and the SoC variations are presented.

C. COMPARATIVE EVALUATION OF RBEMS AND MLBEMS

For both use cases, the performance measures are presented in Table 5. Moreover, in the table, the improvement in percentages is given. For UC1, switching to MLBEMS results in a decrease of 0.4% in terms of SPM. However, the SoC_{Bal} and the BAT_{LT} for the HE and HP batteries are increased by 39.3%, 36.5% and 22.6%, respectively. Similarly, for UC2 SoC_{Bal} and the BAT_{LT} for the HE and HP batteries are increased by 68.6%, 53.6%, and 45.8%, respectively. This significant increase is due to smart power allocation coming from the trained model for higher lifetime and SoC balancing.

TABLE 4. Performance of different MLBEMS using different weighting factors. (N.A: Not applicable).

	ω_{1-2}	SPM	SoC_{RMSE}	BAT_{LT} (HE/HP)
UC1	0.9-0.1	0.9858	0.0150	0.0150 / 0.0110
	0.8-0.2	0.9904	0.0275	0.0146 / 0.0116
	0.7-0.3	0.9920	0.0773	0.0090 / 0.0138
	0.6-0.4	0.9832	0.1380	0.0078 / 0.0120
UC2	0.9-0.1	N.A	0.0138	0.0067 / 0.0031
	0.8-0.2	N.A	0.0205	0.0057 / 0.0032
	0.7-0.3	N.A	0.0614	0.0045 / 0.0039
	0.6-0.4	N.A	0.1806	0.0032 / 0.0039



(a) SoC variation for RBEMS (UC1). (b) Power sharing for RBEMS (UC2). (c) SoC variation for MLBEMS (UC1). (d) Power sharing for MLBEMS (UC2).

FIGURE 7. UC1 and UC2 mission profile power sharing and SoC variation for both RBEMS and MLBEMS.

However, the main reason for such a difference is due to internal power oscillations in the RBEMS. In Fig 7-b the internal power oscillation between HE and HP modules is visible.

TABLE 5. Performance of RBEMS and MLBEMS for both use cases.

	Method	SPM	SoC_{Bal}	BAT_{LT} (HE/HP)
UC1	RBEMS	0.994	0.045	0.023/ 0.015
	MLBEMS	0.990	0.027	0.014/ 0.012
		-0.4 %	39.29 %	36.52 % / 22.58 %
UC2	RBEMS	N.A	0.067	0.012 / 0.006
	MLBEMS	N.A	0.021	0.006 / 0.003
		N.A	68.65 %	53.65 % / 45.76 %

According to the results, MLBEMS outperforms RBEMS in terms of both SoC_{Bal} and BAT_{LT} for all use cases. For UC1, the SoC_{Bal} was increased by almost 40% and the BAT_{LT} by around 20-35%. These improvements are subject to changes in the weight factors in the optimization model. Similarly for UC2, the SoC_{Bal} was increased almost 70% and the BAT_{LT} around 45-55%. One of the reasons for this high difference is the internal power oscillations in the RBEMS.

VI. CONCLUSION

In this paper, a machine learning based EMS (MLBEMS) approach is presented. It aims to replace conventional rule-based EMS (RBEMS) to further improve the SoC balancing and battery lifetime. To compare the methods, two use-cases are selected. The first one is enhanced frequency regulation for the Pan-European grid where the aim is to absorb/supply power from the grid in order to stabilize the grid frequency. The second use case is an EV charging station with PV generation where the aim is to limit the maximum power demand from the grid to 120 kW and limit the ramp-rate to 100 W/s in order to enhance grid stability. The sharp increase in the power demand of the EV charger is supplied by the HESS and the batteries are charged back to their setpoints.

In order to train the model, an optimization model is created. The cost function consists of two parts which are state of charge (SoC) balancing and the consumed life of the HE and HP batteries. The optimization model is run for a wide range of different initial conditions. For each initial point, the optimal power sharing between the HE and HP is determined while ensuring the demanded power from the grid. The generated dataset is provided as input to a Gaussian Isotropic Exponential machine learning regression trainer. The prediction model is fed into the model replacing the RBEMS and runs for both mission profiles.

In conclusion, MLBEMS performs better than the RBEMS in terms of both SoC_{Bal} and BAT_{LT}. In particular, the MLBEMS gives the developer direct control over the lifetime of the overall system. Moreover, MLBEMS allows training externally preferably in a cloud, using real-time system data, and hence the optimal control of the system can be adaptive to aging conditions. A downside is the complexity of the development procedure where accurate battery lifetime modeling requires intensive testing for a long duration. Moreover, developing the overall optimization algorithm and training model requires intensive work. Compared to MLBEMS, RBEMS is simpler in terms of development and code deployment due to the use of conventional controllers and easier to implement in real-time hardware. MLBEMS calculates the optimal power sharing at any given instant and is time independent whereas integrator inside RBEMS may result in system oscillation and stability issues since it accumulates errors from previous time steps. The proposed MLBEMS is also scalable under certain conditions. If the system is scaled by duplicating the exact system then the proposed MLBEMS can be used as local smart EMS maximizing SoC balancing and battery lifetime. However, to allocate the power from the grid to each HESS, a smart higher level power sharing algorithm is required. If different batteries are added to HESS, the study needs to be repeated and the degradation model of the new battery is required. In that sense, it can be concluded that the specific MLBEMS is not always scalable but the proposed method is.

VII. FUTURE WORK

For future work, the RBEMS model control parameters could be modified coupled with additional steps to eliminate the internal power oscillation between the two different batteries. In this paper, a single objective optimization is created and it outperformed RBEMS in terms of SoC_{Bal} and BAT_{LT}. However, the performance of multi-objective optimization study is yet to be performed and investigated. The developed RBEMS and MLBEMS are tested in simulation but the performance of both methods needs to be compared to the actual system.

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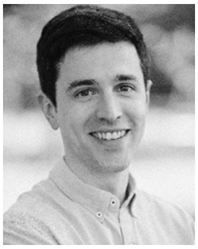
HAKAN POLAT (Member, IEEE) received the M.Sc. degree in electrical machinery and power electronics from Middle East Technical University, Ankara, Turkey, and the Ph.D. degree in engineering science from the EPOWERS-Efficient Power Electronics, Powertrain and Energy Solutions-Research Group, MOBI Research Center, Vrije Universiteit Brussel, Brussels, Belgium, in November 2021. His focus during the M.Sc. degree was finite element modeling and power electronics hardware design. His research interests include reliability, modeling, control, hardware design, and digital twin framework for power electronic systems.



ENEKO UNAMUNO (Member, IEEE) received the M.Sc. and international Ph.D. degrees from Mondragon Unibertsitatea, Mondragón, Spain, in 2014 and 2017, respectively. From March to May 2017, he was a Visiting Researcher with the Department of Engineering Cybernetics, Norwegian University of Science and Technology, Trondheim, Norway. He is currently a Researcher and a Lecturer with the Faculty of Engineering, Mondragon Unibertsitatea. He is the author or coauthor of 12 articles published in international journals with impact factors, ten national and international conferences, and two book chapters. His research interests include the development of modeling, analysis, control, and energy management techniques for ac, dc, and hybrid ac/dc power systems with a large presence of electronic power converters and the integration of distributed, renewable energy-based generation, and energy storage systems into the grid.

DAVID CABEZUELO (Member, IEEE) received the B.S. degree in mining engineering specialized in energy resources from the University of the Basque Country in 2013, the M.S. degree in energy and power electronics from the University of Mondragon in 2015, and the Ph.D. degree in electronics and telecommunications from the University of the Basque Country in 2020. He joined the Electronics and Computing Department, Mondragon University, in 2020. His research background includes electric and hybrid vehicles, variable-speed drives, control strategies, and power converters. His current research areas are oriented to the development of modeling, analysis, control, and energy management techniques and the integration of distributed renewable energy into the grid.

THOMAS GEURY (Member, IEEE) received the master's degree in electrical engineering from Université Libre de Bruxelles (ULB), Brussels, Belgium, in 2012, and the Ph.D. degree in engineering sciences and technology in joint supervision between the ULB (BEAMS Electrical Energy Research Center) and the University of Lisbon (ULisbon), Lisbon, Portugal, from the INESD-ID Power Electronics and Power Quality Group, in 2016, with an FRIA Grant. He also stayed for a few months at the University of Nottingham, Nottingham, U.K. His work focused on a new PV converter topology that uses a matrix converter to solve power quality issues on the distribution grid. He is currently a Postdoctoral Researcher in the field of power electronics and energy management systems with the MOBI-EPOWERS Research Group. His activities involve research and management of EU and national research projects on power electronics, electric and (plug-in) hybrid vehicles, control systems, power management strategies, renewable energy, and storage systems, as well as simulation and modeling.

OMAR HEGAZY (Senior Member, IEEE) received the Ph.D. degree (Hons.) from the Department of Electrical Engineering and Energy Technology (ETEC), Vrije Universiteit Brussel (VUB), Belgium, in July 2012. He is currently the Head of the Efficient Power Electronics, Powertrain and Energy Solutions (EPOWERS) Research Group, Power Electronics Innovation Laboratory (PEIL), Powertrain Innovation Laboratory (PIL), and Joint Smart Charging Laboratory (JSCL), Department of ETEC, and the MOBI Research Centre, where he coordinates the research activities in this field in several national projects, such as Flanders Make, VLAIO (ex. IWT), Innoviris, and Flux50, and European projects, such as SAFEDRIVE, UNPLUGGED, ELIPTIC, ORCA, ASSURED, HiFi-Elements, GHOST, HiPERFORM, CEVOLVER, OBELICS, ACHILES, LONGRUN, eCharge4drivers, iSTORMY, URBANIZED, HiEFFICIENT, NextETRUCK, SiC4GRID, ZEFES, EBRT2030, OpEVA, and NEMOSHIP. He is also the Manager of the MOBI Core-Laboratory, Flanders Make. He is the author of more than 200 scientific publications and two patent applications. His research interests include power electronics, electrical machines, electric and (plug-in) hybrid electric vehicles, digital twin (DT), charging infrastructure, power/energy management strategies, FC (hydrogen) powertrains, battery management systems (BMS), V2X systems, optimization techniques, and smart dc grid with renewable energy. He is a member of EGVIA, EARPA, Inside (ARTEMIS-IA), EPE, SAE, and IEC standards.