Modeling and Optimal Control of Energy Storage System For Battery Life Extension Via Model Predictive Control

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***Abstract*— Islanded microgrids face reliability risks due to renewable energy sources intermittent nature and the varying load demands that could lead to continuous risk of power mismatch in the system. Coupling renewable energy sources (RESs) with advanced energy storage systems, e.g. battery energy storage system (BESS), helps with maintaining the power balance in the system. Limitations persist, in particular regarding the BESS time autonomy, degradation issues and overall costs.**

The paper presents a novel battery aging conscious energy management strategy to control a renewable energy system powered by RESs (wind and solar) and an integrated battery bank for energy storage in the events of excess RESs hours with respect to the user requested electrical load. We design a model predictive controller which takes into account the proposed BESS operating and economical costs, the degradation issues, the local load demand, while respecting system physical and the dynamical constraints. The dynamics of the BESS have been modeled by adopting the mixed-logic dynamic framework which helps in capturing different behaviors according to its possible operating modes. Numerical simulations show the feasibility and the effectiveness of the proposed approach.

***Index Terms*— energy management, energy storage, MPC, optimization, battery management.**

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II. Introduction

During the last decade, the renewable energy sources (RES) have gained considerable attention from the energy community. Wind and solar energies are the most promising options [1]. However, there are some drawbacks associated with them i.e., high installation costs, and their inherent intermittent nature [2]. Over the years, the control engineering and energy community have worked on developing suitable solutions to these issues. One effective solution is leverage on the integration of the energy storage systems with the renewable energy plants [3], [4].

In particular, the battery energy storage system (BESS) integration with the renewable energy plants is the most commonly used storage technology. Batteries have high energy density and can supply average load demand for a long time. Consequently, many efforts have been dedicated to battery storage system characteristics, [5]–[8]. Almost all studies conclude that the batteries may be beneficial in the new energy paradigm, thanks to the faster time response, peak shaving, low operational and maintenance costs.

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However, some issues, specifically robust performances and aging (degradation in life cycles), are slowing the utilization and adoption of batteries as energy storage [3], [9], [10]. Due to the batteries cycle time and power density, high charging/discharging times in micro grid applications are of 0.3-3 hours, [11]. This means frequent charging and discharging cycles, and leads to high and numerous depth of discharge (DOD) cycles. As the average depth of discharge (DOD) and number of cycles increases, the lifetime of the batteries is reduced [12]. It follows that the energy storage efficiency is reduced. Battery degradation, sizing and its associated cost is indeed one of the major concerns when designing energy management strategies of DC microgrids [13]. For this reason, the deployment of an advanced control policy for optimal use of batteries is of paramount importance for the generalization of affordable and reliable RES. For instance, in [14], the authors presented a stochastic multi-microgrid energy management strategy by implementing a chance-constrained programming technique to model the power system uncertainties. One main aspect in life cycle reductions of the batteries is their frequent charging/discharging cycles, which accordingly, was handled with the introduction of the life spans degradation costs in the energy management objective function. Khan et al. [15] presented an MPC based battery energy management strategy to control multiple renewable resources of a microgrid contributing in satisfaction of the user electrical load demand. Elkazaz et al. [16] applied model predictive control (MPC) technique based on mixed integer linear programming (MILP) to control the load sharing of a hybrid ESS composed of PVS, and battery packs also including some degradation issues related to the battery energy management system. However, these studies do not take into account the degradation issues concerning the start-up/shutdown/standby life cycles associated with the batteries.

Consequently, efforts are still needed toward better control strategies for the operations of renewable energy plants with BESSs, especially when multiple objectives have to be addressed simultaneously. In particular, an energy management system (EMS) that takes into account the BESS model, the degradation issues concerning its life span, and minimizes the logical states switching among different operating modes of the battery, is needed. It is pivotal when maintenance, lifetime and price are the most important issues, such as in developing countries. This manuscript presents a first economic battery energy system comprehensive case study that tackles all the previously mentioned points. We design an MPC which takes into account the BESS operating and economic costs, the degradation related to the usage of the batteries.The dynamics of the BESS and its possible operating modes have been modeled using mixed-logic dynamic. The performance of the proposed system, in terms of battery life extension, is compared favorably with the state of the art approaches.

The manuscript is organized as follow: Section III presents the details of the considered microgrid. The control design is detailed in IV. The section V explains and discusses the numerical results of the proposed research. Concluding remarks are offered in Section VI.

III. Microgrid Description

The microgrid under investigation is comprised of a wind generator, solar panels, battery storage, the local loads, and the control and communication systems. A conceptual block diagram is shown in Fig. 1, parameters can be found in [3], [17], [18]. In Table 1, the different degradation processes considered by the controller are summarized.

TABLE 1: Considered degradation issues for the ESS.

Energy Storage System	Degradation Issues
Battery Storage	Number of working hours Operation and Maintenance Costs Start/Stop/standby Cycles Fluctuations of current

Under nominal conditions, the powers from the wind generator P_w, and the PV generator P_{PV} are delivered directly to the load demand. However, when an excess of RE power production happens, it is shunted to the battery pack. Conversely, whenever the RESs can not satisfy the load demand, the battery is used as a backup power source, thus achieving power supply continuity.

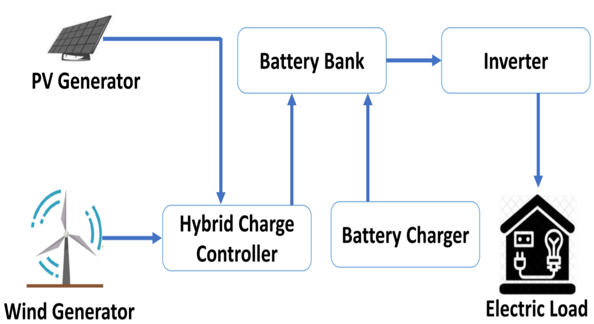

Fig. 1: Microgrid object of this study.

IV. Controller Design

In this paper, we tackle the optimal operation planning of a BESS to match power demand through the system available power P_{avl}. The novelty of the approach is considering the degradation issues associated with the battery energy storage, in order to minimize the frequent charging and discharging battery cycles, leading to improving the battery life span. The optimization problem is developed and solved with the use of MPC policy [19].

The block diagram of the controller is detailed in Figure 2. The controller was implemented in Matlab using the solver GUROBI[1].

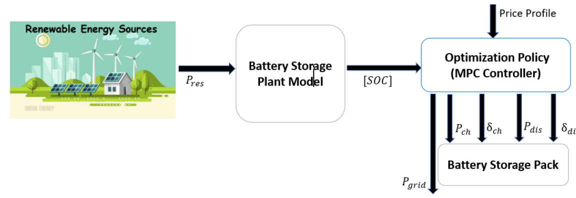

Fig. 2: MPC Controller.

A. State Space Model of the BESS

The battery storage dynamics are defined as a function of the state of charge SOC at the previous time step SOC(k) [3], and is modeled as a dynamic equation:

$$\begin{aligned}\mathrm{SOC(k+1)} &= \mathrm{SOC(k)} + \eta_{\mathrm{ch}}\mathrm{(k)P_{ch}(k)}\delta_{\mathrm{ch}}^{\mathrm{CH}}\mathrm{(k)T_s} \\ &- \frac{P_{dis}(k)\delta_{dis}^{\mathrm{DIS}}(k)T_s}{\eta_{dis}(k)},\end{aligned} \tag{1}$$

where T_s denotes the sampling period. The $\eta_{\mathrm{ch}}(k)$ and $\eta_{\mathrm{dis}}(k)$ represent battery charging and discharging efficiencies with respect to the degradation. The battery produces and consumes electrical energy only in its charging/discharging modes. All the other modes are not associated with the energy production and consumption thus, are not associated to efficiency degradation.

B. Proposed MPC Formulation

According to the MPC scheme, at each instant k, a sequence of future command inputs is selected by the controller, spanning a time horizon. The selection relies on an optimization procedure, that minimizes the cost function which encompasses the fulfillment of the constraints. Only the first sample of the control sequence is considered, and subsequently, the horizon is shifted, [19].

The global cost function to be minimized by the MPC controller is:

$$J(k) := \sum_{j=1}^{T}\Big(\omega_{\mathrm{b}}J_{\mathrm{b}}(k+j) + \omega_l J_{\mathrm{l}}(k+j)\Big), \tag{2}$$

where $J_{\mathrm{b}}(k)$, and $J_{\mathrm{l}}(k)$ are the battery, and load demand tracking cost functions, respectively. We wish to highlight here that $b \in\{\mathrm{ch}, \mathrm{dis}\}$ are the charging and discharging states of the battery. ω_{b}, and ω_l are the weighting factors used to achieve meaningful and dimensionless operations of the cost functions regardless of their unit measures. In the next subsections, the cost function J and its components J_b, and J_l will be presented in more detail.

[1] https://www.gurobi.com/

B.1. Battery Cost Function: The battery cost function for operating costs minimization include various terms that take into account for the battery aging, life hours reduction, and stand-by state energy consumption. The significant variations in electrical loads along with the operating cycles can severely damage the batteries through many ways [3]. The battery charging/discharging models in this research study can be operated in 3 different physical modes, namely the charge/discharge, no charge/discharge and the standby modes. In order to improve readability of the proposed battery models, we introduce here some notations that will be used throughout the paper. The set $\mathcal{I} = \{\mathrm{ch}, \mathrm{dis}\}$ and the index $b \in \mathcal{I}$ will indicate the battery charging (ch) or the discharging (dis) state. Similarly, we define the sets $\mathcal{A} = \{\mathrm{NO-CH/DIS}, \mathrm{STB}, \mathrm{CH/DIS}\}$ that will represents the transition between the battery modes, including the standby one.

Our proposed cost function is:

$$\begin{aligned} J_b(k) := &\left(\frac{CC_{\mathrm{bat}}}{\mathrm{Cycles_{bat}}}\right)\delta_b^{\mathrm{CH/DIS}}(k) \\ &+ \mathrm{Cost}_{\alpha,b}^{\beta}\sigma_{\alpha,b}^{\beta}(k), \end{aligned} \tag{3}$$

where $\alpha, \beta \in \mathcal{A}$, and $\alpha \neq \beta$, k is the current time instant, CC represents the battery capital cost, and the $\mathrm{Cost}_{\alpha_b}^{\beta}\sigma_{\alpha_b}^{\beta}(k)$ denote the cost associated with the battery switching modes. Additionally, in equation (3), a series of auxiliary logical variables have been introduced. Further to the above, the battery mode switching has been handled in terms of logic commands [20]: each battery state is linked to a logic variable [2] $\delta_b^{\alpha}(k) \in [0, 1]$, where $\alpha \in \mathcal{A}$, so that $\delta_b^{\alpha}(k) = 1$ whenever for a given $b \in \mathcal{I}$, the corresponding b is in state α at time-step k, $\delta_b^{\alpha}(k) = 0$ otherwise. Similarly, each state transition is also linked to a logic variable $\sigma_{\alpha,i}^{\beta}(k) \in [0, 1]$, where $\alpha, \beta \in \mathcal{A}$, so that $\sigma_{\alpha,b}^{\beta}(k) = 1$ whenever for a given $b \in \mathcal{I}$, the corresponding b state is switching from the state α to the state β at time-step k. Otherwise, $\sigma_{\alpha,b}^{\beta}(k) = 0$.

B.2. Battery mode logical expressions: For the battery in charging state, the corresponding charging power is bounded within the range $[P_{\mathrm{ch}}^{\min},\ P_{\mathrm{ch}}^{\max}]$. Therefore, by defining $P_{\mathrm{ch}} = P_{\mathrm{ch}}(k)\delta_{\mathrm{ch}}^{\mathrm{CH}}(k)$, it results that $P_{\mathrm{ch}} = P_{\mathrm{ch}}(k) \in [P_{\mathrm{ch}}^{\min},\ P_{\mathrm{ch}}^{\max}]$ when $\delta_{\mathrm{ch}}^{\mathrm{CH}}(k) = 1$. Thus, being mutually exclusive, all other logical variables $\delta_{\mathrm{ch}}^{\alpha}$, $\alpha \neq \mathrm{CH}$ are null.

Additionally, in the STB mode, the corresponding power is $P_{\mathrm{ch}}^{\mathrm{STB}}$. By defining $P_{\mathrm{ch}}^{\mathrm{STB}} = P_{\mathrm{ch}}(k)\delta_{\mathrm{ch}}^{\mathrm{STB}}(k)$, it follows that $P_{\mathrm{ch}}^{\mathrm{STB}} = P_{\mathrm{ch}}(k)$ when $\delta_{\mathrm{ch}}^{\mathrm{STB}}(k) = 1$. Again, all other logical variables $\delta_{\mathrm{ch}}^{\alpha}$ with $\alpha \neq \mathrm{STB}$ are null.

Finally, the battery in the No-CH state has $P_{\mathrm{No-ch}}(k) = 0$, along with null power consumption (no energy production happens in this status). In general $P_b^{\alpha} = P_b\delta_b^{\alpha}(k)$, therefore, according to the operating condition of the battery, each $\delta_b^{\alpha}(k)$ can be determined following:

$$\begin{cases} P_b^{\min} \leq P_b(k) \leq P_b^{\max} & \Longleftrightarrow \quad \delta_b^{\mathrm{CH/DIS}}(k) = 1, \\ P_b(k) = P_b^{\mathrm{STB}} & \Longleftrightarrow \quad \delta_b^{\mathrm{STB}}(k) = 1, \\ P_b(k) = 0 & \Longleftrightarrow \quad \delta_b^{\mathrm{No-CH/DIS}}(k) = 1. \end{cases} \tag{4}$$

The modeling approach followed in this paper consists in deriving a mixed-integer formulation of the operating constraints and logical devices states ($\delta_b^{\alpha}(k)$) so as to be included in a MPC controller and numerically solved. However, the logical expressions in Eq. (4), being non linear, cannot be handled by numerical solvers as they are. Instead, they require further manipulation to derive equivalent mixed-integer inequalities. To do so, as an intermediate state, based on the three logical states of the battery, six 6 auxiliary Boolean variables can be defined as deriving an equivalent (Eq. (4)) mixed-integer inequality. The Boolean variables will then be utilized to achieve an equivalent big-M formulation, [20].

Since the battery will work in one and only one mode at any time k, the additional constraint

$$\delta_b^{\mathrm{NO-CH/DIS}}(k) + \delta_b^{\mathrm{STB}}(k) + \delta_b^{\mathrm{CH/DIS}}(k) = 1 \tag{5}$$

has to be considered.

The transitions among states can be defined by suitably combining logical variables with standard logical connectives. According to the number of states, there are 6 possible mode transitions. The resulting inequalities have been derived and provided as constraints in the proposed MPC controller:

$$\sigma_{\alpha,b}^{\beta}(k) = \delta_b^{\alpha}(k-1) \wedge \delta_b^{\beta}(k), \tag{6}$$

where $\sigma_{\alpha,b}^{\beta} \in [0, 1]$.

Once again, the non-linearity between the product term of the two logical states as derived in Eq. (6) can be resolved with the help of the equivalent big-M formulation, [20].

C. The battery lifetime quantification method

An important aspect of the battery energy storage system design is its life-span. The battery life time quantification method has been reported in the literature to be accurate [21], and is used in this manuscript. As shown in Fig. 2, the BESS drives the battery state of charge (SOC), based on the available RES generations and the electrical demand. That SOC profile works as an input for the battery lifetime model developed in this subsection. In particular, the calculation of the battery cycles is key to estimate the battery lifetime. The BESS shallow cycle is defined as a single partial charging/discharging cycle. The constraints in Eq. (7) are used to determine the BESS partial cycles. When the value of the binary discharging state $\delta_{\mathrm{DIS}}(k)$ changes from 1 to 0 and to 1 again, one partial cycle has been performed. The value of partial cycles (P_c) will be 1 every time the discharging process is initiated, otherwise it is 0, following [22].

$$\begin{aligned} \delta_{\mathrm{DIS}}(k) - \delta_{\mathrm{DIS}}(k-1) = 1 &\implies P_c(k) = 1, \\ \delta_{\mathrm{DIS}}(k) - \delta_{\mathrm{DIS}}(k-1) \leq 0 &\implies P_c(k) = 0. \end{aligned} \tag{7}$$

[2] Both the variable δ_b^{α} and $\sigma_{\alpha,b}^{\beta}$ are defined in the whole interval $[0, 1]$. The constraints introduced later will force them to take values only at the boundaries of the interval.

C.1. Depth of Discharge: DOD is generally defined as the ratio of the discharged energy to the rated capacity, [22]. Based on the obtained optimal rated capacity of BESS, the formula shown in Eq. (8) is developed and used to calculate the optimal depth of discharge at each time interval. The maximum DOD value over the planning time horizon is the optimal maximum value as shown in Eq. (9). The maximum DOD is limited by the operating range of the battery specified by the system planner (80% in this study).

$$\mathrm{DOD(k)} = 1 - \mathrm{SOC(k)}. \tag{8}$$

$$\mathrm{DOD_{max}} = \max(\mathrm{DOD(k)}). \tag{9}$$

The SOC of the BESS is the ratio of the current energy capacity of the BESS to its rated energy capacity. Since a discharge varies in depth, the optimal depth of discharge at each counted partial discharge cycle at time interval k depends on the DOD at the previous time, $k-1$ and the DOD at the period k, as given in Eq. (10):

$$\mathrm{DOD_{P_c}(k)} = \mathrm{DOD(k)} - \mathrm{DOD(k-1)}. \tag{10}$$

C.2. Estimation of BESS Lifetime: We use Miner's rule, following [21], [23], to estimate the aging of the battery. The summation of the BESS partial cycles, N_{cycles} over the planning time horizon (24h, or one day, in the present work) is compared to the maximum number of cycles CF, as provided by the manufacturer.

$$\mathrm{BESSaging} = \frac{N_{cycles}}{\mathrm{CF}} \tag{11}$$

The number of cycles to failure CF at maximum $\mathrm{DOD} = 100\%$ is usually around 3000 for Li-ion batteries.

The estimate of the number of performed partial cycles is done by summing, for each discharge $\mathrm{DOD_{P_c}}$, the corresponding fraction of numbers of cycles to failure CF_{P_c} at $\mathrm{DOD_{P_c}}$. Essentially, it means associating any discharge to a fraction of a complete cycle:

$$N_{cycles} = \sum_k P_c(k)/CF_{P_c}(k). \tag{12}$$

The number of cycles to failure (CF_{P_c}) depends on DOD_{P_c} and is obtained from the relation between life cycle and depth of discharge. This relation is usually provided by the manufacturer of the adopted battery technology, as illustrated in Fig. 3b.

Finally, the lifetime BESSLifetime of the battery, in years, is simply the inverse of the BESSaging:

$$\mathrm{BESSLifetime} = \frac{1}{365 \times \mathrm{BESSaging}}. \tag{13}$$

Estimating the number of complete discharge cycles is done by comparing the BESSLifetime of a battery system to its maximum number of discharge cycles, as given by the manufacturer. The number of complete cycles per year NCC is calculated as:

$$\mathrm{NCC} = \frac{\mathrm{CF}}{\mathrm{BESSLifetime}}. \tag{14}$$

D. System Constraints

In order to achieve a realistic optimal control policy, the energy balance equation must be satisfied at each time-step k. Similarly, the battery pack has a limitation in the power that it can absorb or provide, and the SOC is bounded. Thus, the following equality constraint will be also included:

$$\begin{aligned} P_{\mathrm{avl}}(k) &= P_W(k) + P_{\mathrm{PV}} \\ &\quad + P_{dis}(k)\delta_{dis}^{\mathrm{DIS}}(k) - P_{ch}(k)\delta_{ch}^{\mathrm{CH}}(k) \end{aligned} \tag{15a}$$

$$P_{\mathrm{min,b}} \leq P_b(k) \leq P_{\mathrm{max,b}} \tag{15b}$$

$$SOC_{\mathrm{min}} \leq SOC(k) \leq SOC_{\mathrm{max}}. \tag{15c}$$

E. Electrical Load Tracking Cost Function

One control goal of the proposed controller is the tracking of the requested demand P_{load}. To achieve this, the controller will also minimize the cumulative squared error between P_{load} and P_{avl}:

$$J_l(k) := \sum_{j=0}^{T-1} \Big(P_{\mathrm{avl}}(k+j) - P_{\mathrm{load}}(k+j)\Big)^2. \tag{16}$$

V. Simulations

The MPC controller developed in previous sections has been implemented and simulated in MATLAB/YALMIP using GUROBI optimizer. For simulations, the parameters affecting the cost functions used by the optimizer have been chosen as reported in Table 3.

We performed simulations for a periodic 24 hour horizon. It is worth writing here that our main contribution of the manuscript relies in developing preliminary operating models needed for running the battery-based ESS for long control periods. In addition, answering the energy demand remains the aim of the system. The controller track the electrical reference as per the amount of available energy in the system through renewable sources and battery SOC. In order to show the control strategy effectiveness in terms of battery cycle maximization, the proposed control strategy, with inclusion of battery standby model, is compared with standard, literature based approaches [3], [21], [24].

A. Simulations without Battery standby state model

In the scenario under consideration, the frequent variations of the electrical load demand with respect to the renewable energy generations have been considered. In particular, Fig. 3a illustrates the frequent imbalance of the renewable generations and the user requested electrical load demand. It is possible to notice in Figs. 3c and 3d, that after meeting the load, the excess of energy is shunted towards to the battery pack. Figs. 3c and 3d also illustrate the battery switching with respect to its charging and discharging states, respectively.

It is observable from Fig.4a, the controller at each time-step k successfully tracks the electric demand in all 24 hours of the day with the system available power.

The associated $\mathrm{DOD_{P_c}}$ of the partial cycles performed by the battery is depicted in Figs. 3e and 3f. Using the Eqs. (12) and (13), the battery life time for the standard approach

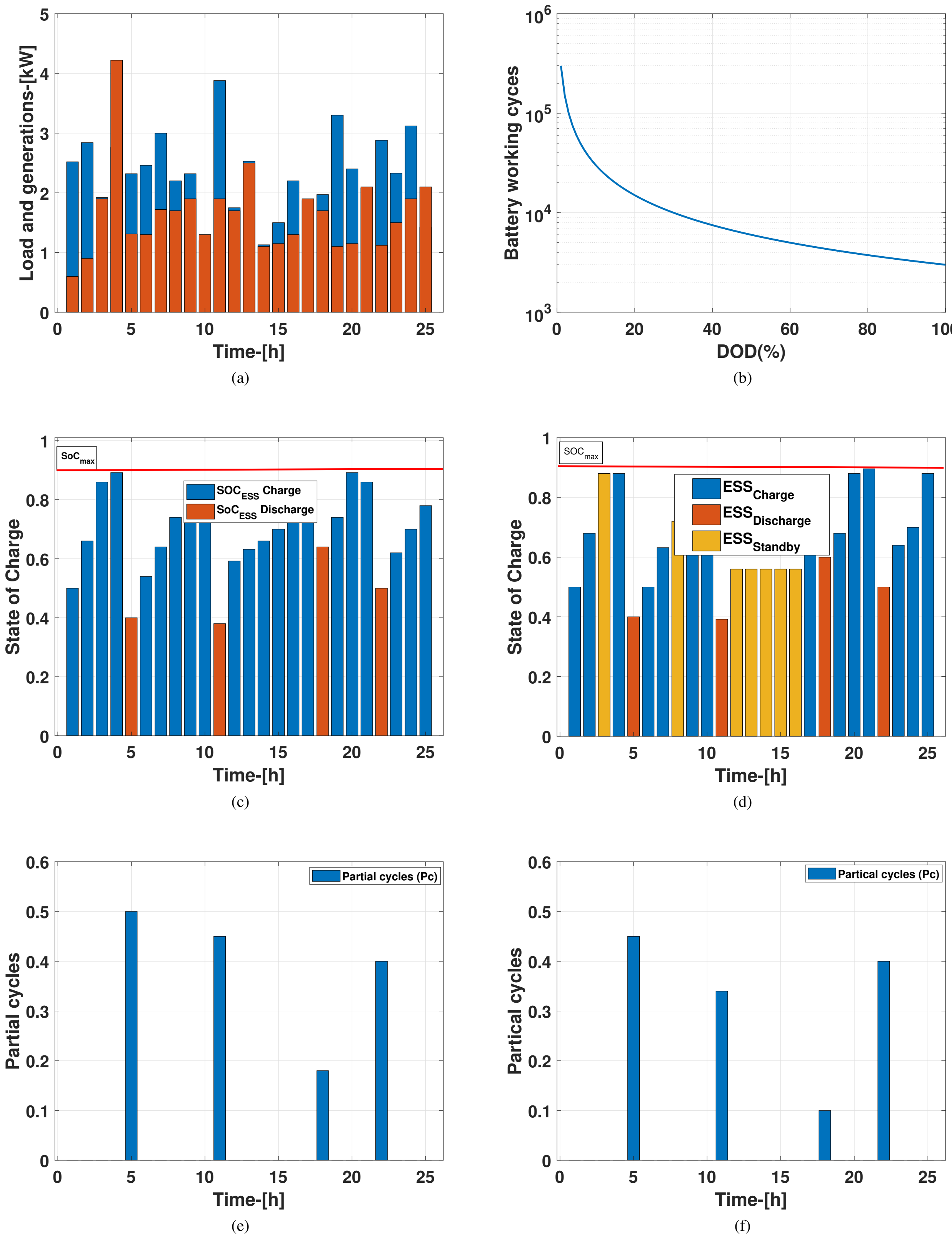

Fig. 3: Numerical results. (a): Renewable generations and Load Demand. (b) Battery number of complete working cycles with respect to the DOD. (c) Battery SOC and mode, with literature approach. (d) Battery SOC and mode, with proposed control. (e): Partial cycle Pc with literature approach. (f): Partial cycle Pc with proposed control strategy.

TABLE 2: Results Comparison.

Approach	Battery working cycles	BESSlifetime	Completed cycles/year	Average DOD	Life extended (years)
Literature approach [3], [21]	3000	19.7	152.28	36.04%	-
Present approach	3000	25.3	118.57	32.1%	5.6

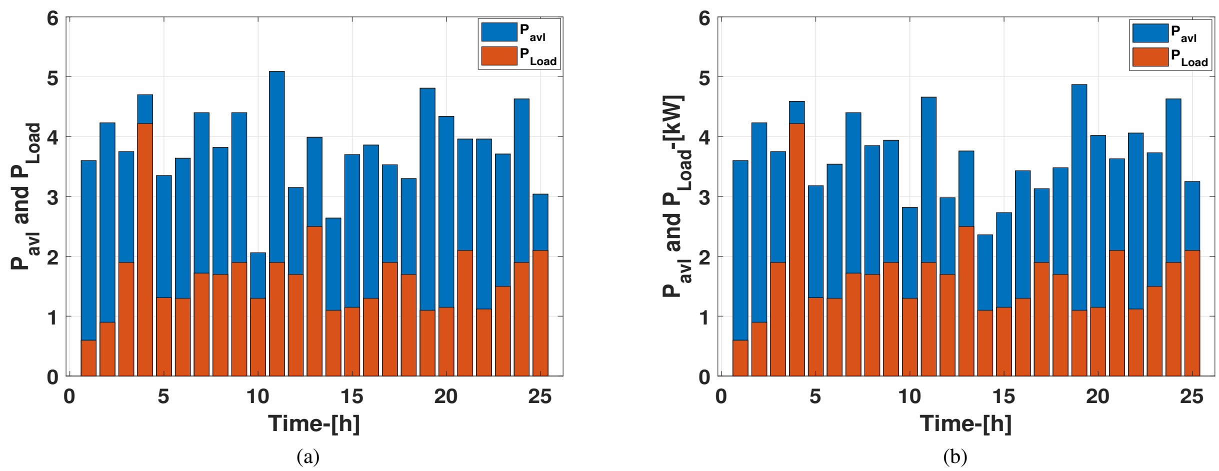

Fig. 4: System available power and demand. (a): standard approach. (b): optimized approach.

TABLE 3: MPC parameters.

Li-Ion battery parameters	
$\eta_{\rm ch} = 0.90$	$\eta_{\rm dis} = 0.95$
$CC_{\rm bat} = 125\,£/\rm kWh$	$\rm Cycles_{bat} = 3000$
$\rm Cost^{CH/DIS} = 0.055\,£$	$\rm Cost^{No-CH/DIS} = 0.055\,£$
$\rm Cost^{STB} = 0.0275\,£$	$P_b^{\rm min} = 0.2\,\rm kW$
$P_b^{\rm STB} = 0.2\,\rm kW$	$P_b^{\rm max} = 5\,\rm kW$
$\omega_b = 0.666$	$\omega_l = 0.334$

is calculated, with $\text{BESSlifetime}_{stand} = 19.70$ years. Using Eq. (14), the equivalent complete number of cycles per year performed by the battery system is $\text{NCC}_{stand} = 152.28$ cycles/year. This is based on the maximum optimal DOD of 80%. It corresponds to an average of 0.41 complete cycles/day.

B. Simulations with Battery standby state model

The MPC controller implemented on the novel battery model with the inclusion of the standby state is able to successfully track the electrical reference throughout the day as illustrated in Fig. 4b.

The excess of energy after meeting the load demand is stored in the batteries as shown in Fig. 3d to be used as a backup source during low or nearly zero RES hours. The battery logic state switchings can also be seen from Fig. 3d.

Likewise, in the battery simulations, the associated DOD_{pc} of the partial cycles performed by the battery is depicted in Fig. 3f. Based on these consumed partial cycles, the BESS life time in years has been calculated as in Eq. (12), and (13) . The lifetime of the BESS via proposed control strategy is $\text{BESSlifetime}_{opt} = 25.3$ years. Similar to what has been calculated with the standard approach, the equivalent complete number of cycles per year in the proposed control strategy performed by the battery is computed based on the maximum optimal DOD of 80%. The NCC_{opt} is found to be 118.57 complete cycles/year (averaging 0.33 complete cycles/day).

With the proposed approach, the power needs are fulfilled, while frequent charging/discharging events have been minimized. The lifetime of the energy storage is increased almost by 28% when compared to the standard approach.

C. Comparison with respect to the battery life

This subsection summarizes the performance of the proposed novel battery model with the standard approach, and the results are summarized in Table 2. The parameters taken in the comparison process are the battery working cycles, BESSlifetime, completed cycles per year, completed cycle per day, and the life time extension of the battery energy storage system.

Both the controllers were able to meet the electrical reference perfectly, but the frequent charging/discharging battery events can be clearly seen from the simulations carried out without incorporating the standby state battery and cost models as shown in Fig. 3c. Moreover, Fig. 3c also reflects the battery switching modes (charging and discharging) under regular literature based approach over 24 hour simulation. On the other hand, the number of charging/discharging battery events are reduced (see Fig. 3d) through the MPC implementation of the proposed strategy. It is possible to notice that during the hours 12-16, the controller switches the battery to its charge state, and a slight increase in the battery SOC with respect to the $k-1$ can be seen from Fig. 3c. This results in frequent charge cycles consumption of the battery life. The controller allows the battery to remain in standby state up to 37.5% of the time, as seen in Fig. 3d. The use of the standby state in the battery models combined with considering the partial cycles in the cost function have led to savings in battery life cycles, thus maximizing its lifetime.

One objective is to restrict/avoid slight charge/discharge battery events. Indeed, in Fig. 3d, during hours 12-16, the controller did not switch the battery to its charge state, rather, it pushed the battery in the standby or idle state. The mode switchings of the battery under the proposed MPC controller has also been shown in Figs. 3c and 3d. It can also be seen that the battery is not fully charged under our policy, which minimizes the stress on the battery.

The second objective is to restrict/avoid deep discharge battery events. Indeed, in Fig. 3d, during hours 3-5, the controller did not switch the battery to its charge state, rather it pushed the battery in the standby or idle state. Consequently, partial cycles are less deep. It can be seen that the amplitude of discharge is limited when using the proposed approach, see Figs. 3e and 3f. The average DOD for the standard approach is 36.04%, compared to 32.1% with our approach. The simulations proved that, with the help of the implementation of the proposed control system, the battery life in comparison to the literature based studies, has been extended to almost 5.6 years with the saving of almost 33.71 complete cycles/year.

The battery improved performance has practical effects. When comparing Figs. 3c and 3d, the available capacity is higher before expected high demand times, and lower before high generation times. This means that the microgrid flexibility is improved. Additionally by reducing the charge events, the integrity of the battery is improved, and the operation and maintenance costs are reduced, when compared to the standard approach.

VI. Conclusion

In this manuscript, we proposed an MPC control strategy for a battery-based ESS integrated in a RES facility. The proposed MPC scheme takes into account the cost that the battery model introduces at each time it switches between different operating modes, thus decreasing the corresponding number of life cycles and efficiencies. Moreover, all the system operational and physical limitations, such as the battery power consumption in their standby states, are considered. The costs related to the operations of BESS and the developed mixed logic dynamic model have been included in a MPC scheme. The proposed MPC was compared with standard literature based approaches. The results demonstrate that the presented approach provides better cost savings and maximized the lifetime of BESS by almost 28%. Simulations have been carried out by tracking reference power provided by the local load demand, during 24 hours test runs. Correct working operations of the BESS and its different operating modes have been validated through numerical results. An extra business feature of energy market participation through utility grid interaction for the solar and the wind farm owners has also been considered in the proposed research study, and will be reported in a subsequent manuscript. Future works will integrate the proposed results into a multi timescale BESS power regulation market, and deploy the control strategy to the Birmingham City University laboratory microgrid.

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