MPC-based Management of Energy Resources in Smart Microgrids

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Abstract: This paper presents a model predictive control approach for the economic optimization of a microgrid including smart buildings, wind power production facilities and an energy storage unit. Various optimization scenarios are considered in a comprehensive and unified framework, which can be adapted to pursue different objectives at the same time, such as ensuring the electricity supply to the smart buildings, maximizing the profit from the electricity trading market, or managing the energy storage. The optimization problem can be addressed in a model predictive framework using the receding horizon approach, and ultimately formulated as a quadratic programming problem, which can be solved with reliable and efficient tools. In order to analyze a realistic scenario, the relevant data are taken from real systems (i.e., from a real wind farm and from a real commercial building, located in Italy). Simulation results show the economic advantages that can be gained through the combined usage of renewable energy generation and energy storage.

1 INTRODUCTION

The increase in the cost of energy produced with conventional fossil fuels and the growing concern for the environmental problems related with their usage have fostered the interest in alternative energy sources, such as Renewable Energy Sources (RES), to be placed in the vicinity of the end users, thus reducing the energy losses. This entails a radical change towards the concept of microgrid. Microgrids are relatively small electricity networks, that can include any type of distributed energy resources, as well as consumption and storage elements.

The development of optimal control solutions for microgrids has been the objective of several recent research endeavors, employing, *e.g.*, heuristic algorithms (Gu et al., 2010), or genetic algorithms (Nemati et al., 2015). One particularly exploited methodology in this context is Model Predictive Control (MPC), which is well suited to deal with the large amount of constraints and multiple objectives that have to be imposed in real time and the tight performance requirements associated to these systems.

For example, the MPC approach has been applied to the problem of optimally dispatching power to the grid in (Teleke et al., 2010); the problem of energy management in microgrid in (Parisio et al., 2014), , (Clarke et al., 2016), (Ferrarini et al., 2014), (Silvente et al., 2015). Among these papers, the formulations considered in (Parisio et al., 2014), (Silvente et al., 2015), and (Clarke et al., 2016) all exploit a combination of MPC and Mixed Integer Linear Programming (MILP). A more comprehensive case is studied in (Parisio et al., 2014) that includes ESS units, RESs, distributed generators and (partially) controllable loads. The general problem formulation takes into account various factors, such as different charge/discharge efficiencies in the ESS elements, electricity trading with the grid (with different purchase and sale prices), start-up and shut-down costs of the distributed generators, operating and maintenance costs of the ESS elements and the distributed generators. The RESs considered in that work are of the photovoltaic type, which allow a good short-term prediction (Accetta et al., 2012), as opposed to wind generators.

This paper proposes an MPC approach for the economical optimization of a microgrid equipped with wind power sources, an ESS and a smart building, that interacts with the energy market. The battery controller is designed to maximize the economic benefit related to the electricity trading on the market, taking into account various types of

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penalties imposed to electricity suppliers. In particular, innovative contributions are the use of a detailed model of the electricity trading conditions, that includes both imbalance charges (with relative tolerances) and load curtailment penalties, and the use of a nonlinear model for the ESS, that includes charge/discharge efficiency curves. This research extends the study presented in (Ferrarini et al., 2014) to a more general microgrid energy management scenario with controllable loads (in a demand response perspective), endowed with storage and generation facilities. Various objectives, grid-, comfort- or economic-oriented, can be pursued. To focus on the main power flows, the microgrid is simplified by aggregating the loads, the generation units, and the storage systems, respectively. The optimization problem is solved in the MPC framework using standard quadratic programming (QP) tools, as opposed to other approaches which use MILP (and require suitable simplifications of nonlinear terms) (Parisio et al., 2014).

The rest of the paper is organized as follows. The microgrid setting and considered scenarios are described in Section 2, the corresponding model being explained in Section 3. The control architecture and algorithms are introduced in Section 4. Simulation results are illustrated in Section 5 before the concluding remarks (Section 6).

2 MICROGRID SYSTEM AND SCENARIOS

2.1 System Description

The microgrid considered in this paper (see Fig. 1), comprises a smart building (*i.e.*, a large load representing, *e.g.*, a large industry, an airport, a shopping district, a commercial building, or several building blocks), a RES (*e.g.*, a wind farm) and an ESS (a battery). All components are connected on the same electricity bus and linked with the main grid by a Point of Common Coupling (PCC), assumed always closed (grid-connected mode). The electricity required by the load can be taken from either the RES or the ESS, or purchased from the grid. The excess electricity generated by the RES or stored in the ESS can also be sold to the grid.

Battery charging and discharging is managed by an MPC-based controller, that receives as inputs the predicted production of the RES, the load demand, the electricity tariffs, and aims at the minimization of the total energy cost of the microgrid. Moreover, the control system is designed to fulfill all the relevant operating constraints, namely the bounds on the maximum charge/discharge power, and on the maximum and minimum energy levels allowed for the battery, as well as the maximum deviation on the load profile tracking.

A smart building is endowed with some flexibility in the tracking of the load demand. For example, a flexible load control system is developed in (Ferrarini and Mantovani, 2013) and (Mantovani and Ferrarini, 2015), that pursues a threefold objective, namely energy cost minimization, temperature regulation (at each floor), and load tracking. For simplicity, we do not here include the load control system, while still allowing for some flexibility in the load tracking for demand-response scenarios. As discussed later on, the level of flexibility is established by way of an interaction and negotiation process between the load and the microgrid energy manager in charge of the battery. The present paper focuses solely on the control design for the battery system in the microgrid.

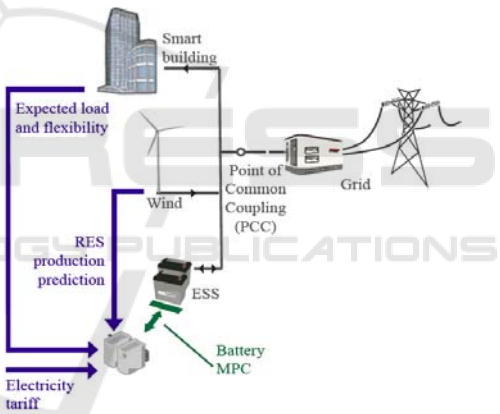

Figure 1: Considered microgrid, with a single PCC.

2.2 Control Objectives

The paper provides a general, comprehensive framework for the modeling and control of microgrids to be designed to pursue a trade-off between different objectives. The main control objectives are listed below:

- *Energy cost minimization* – The battery must supply the load with the required electrical energy, exploiting the RESs and operating the microgrid at the minimum possible monetary expense, based on the knowledge of purchase and sale tariffs and the (estimated) future RES production in the considered prediction horizon.
- *Minimization of imbalance charges* – Energy

exchanges with the grid are regulated by a negotiation (performed on a daily basis) with the utility provider, that sets a power profile (*i.e.*, day-ahead production) and relative tolerances, the violation of which results in monetary penalties.

- *Optimal load curtailment* – The load power profile can be modified (within tolerance bounds specified by the load side), at a cost (curtailment penalty), in the interest of the entire microgrid.
- *Smoothing of the power flow* – Abrupt changes in the power flows may damage the building actuators and adversely affect the power quality or even the grid reliability.

Furthermore, the control system takes into account the nonlinear characteristics of the battery. The multi-objective optimization problem is formulated by introducing suitable coefficients for the individual objectives, whose tuning modulates the focus of the MPC. The latter is constrained by the battery operating conditions, such as peak power and state of charge bounds.

3 MODEL FORMULATION

3.1 Power Balance Equation

The power flow in the microgrid is described by the power balance equation:

$$P_i^{pcc} = -P_i^b - P_i^w + P_i^l, \tag{1}$$

where i is the discrete time step, P_i^{pcc} is the incoming power flow at the PCC, P_i^b is the power supplied by the battery, P_i^w is the power produced by the wind turbine, and P_i^l is the electrical power absorbed by the load, all power variables being measured in kW. Furthermore,

$$P_i^b = P_i^{b,d} - P_i^{b,c}, \tag{2}$$

$$P_i^{pcc} = P_i^{pcc,B} - P_i^{pcc,S} \tag{3}$$

where $P_i^{b,d} \geq 0$ and $P_i^{b,c} \geq 0$ denote the battery discharging and charging powers, respectively, and $P_i^{pcc,B} \geq 0$ and $P_i^{pcc,S} \geq 0$ denote the purchased and sold powers, respectively. Since imbalance charges are inflicted only for violations of the planned power exchanged at the PCC of a given percentage, P_i^{pcc} is further re-elaborated as:

$$P_i^{pcc,B} = \bar{P}_i^{pcc,B} + \Delta P_i^{pcc,B} \tag{4}$$

$$P_i^{pcc,S} = \bar{P}_i^{pcc,S} + \Delta P_i^{pcc,S} \tag{5}$$

where $\bar{P}_i^{pcc,B} - \bar{P}_i^{pcc,S}$ (with $\bar{P}_i^{pcc,B}$, $\bar{P}_i^{pcc,S} \geq 0$) denotes the main component of P_i^{pcc}, that is allowed to deviate at most of 20% with respect to the planned power, and $\Delta P_i^{pcc,B}$ and $\Delta P_i^{pcc,S}$ account for possible additional deviations that result in imbalance charges being inflicted. Only one of these deviation terms at a time can be strictly positive (if the 20% tolerance is exceeded). This fact can be ensured since both $\left(\Delta P_i^{pcc,B}\right)^2$ and $\left(\Delta P_i^{pcc,S}\right)^2$ are minimized in the overall optimization problem. In the best case when such values equal to zero, the power deviations up to 20% are tolerated without imbalance costs. To account for load curtailment penalties, the electrical power P_i^l absorbed by the load is further divided into three parts:

$$P_i^l = \bar{P}_i^l + \Delta P_i^{l,u} - \Delta P_i^{l,l}, \tag{6}$$

where $\bar{P}_i^l \geq 0$ is the load demand defined by the load side, while $\Delta P_i^{l,u} \geq 0$ and $\Delta P_i^{l,l} \geq 0$ account for the positive and negative differences between P_i^l and $\bar{P}_i^l$, respectively (note that only one of this terms can be different from 0 at any time instant). Curtailment penalties are inflicted only if $\Delta P_i^{l,u}$ or $\Delta P_i^{l,l}$ are strictly positive. Overall, the power flow balance equation can be rewritten as follows:

$$\begin{aligned} \bar{P}_i^{pcc,B} = \bar{P}_i^{pcc,S} - \Delta P_i^{pcc,B} + \Delta P_i^{pcc,S} - P_i^{b,d} + \\ P_i^{b,c} + \bar{P}_i^l + \Delta P_i^{l,u} - \Delta P_i^{l,l} - P_i^w. \end{aligned} \tag{7}$$

3.2 State of the Battery Charge

Common simplistic assumptions on the battery model consider ideal (*e.g.*, constant) charge/discharge efficiencies. However, the internal resistance of the battery changes with respect to State Of Charge (SOC) level, thereby increasing the internal losses (and reducing efficiency). Accordingly, a more realistic setting requires that the efficiencies be assumed dependent on the SOC levels, which ultimately results in a nonlinear model:

$$\begin{aligned} SOC_{i+1} = SOC_i - \frac{P_i^{b,d} T_s}{\eta_D(SOC_i) C_b} \\ + \frac{\eta_C(SOC_i) P_i^{b,c} T_s}{C_b} \end{aligned} \tag{8}$$

where SOC_i is the SOC at time step i [%], η_D and η_C are the discharge/charge efficiency functions, respectively, C_b is the battery capacity [kWh], and T_s

is the sampling time. For simulation purposes the quadratic efficiency functions shown in Fig. 2 have been employed.

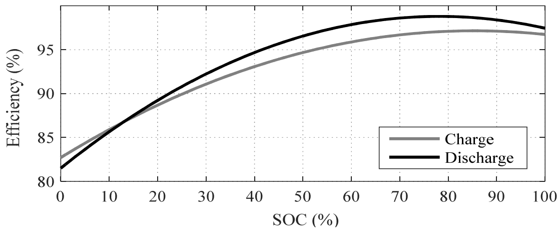

Figure 2: Typical battery efficiency curves.

4 MPC BATTERY CONTROL

4.1 Output Prediction

In the MPC setting the control optimization is performed over a given future time horizon, and, according to the receding horizon principle, only the first control action is applied and the optimization is repeated at the next time step. The optimization requires the prediction of the output based on future control moves over the considered time horizon. Referring to equation (7) we will set the output variable to $y_i = \bar{P}_i^{pcc,B}$ and define the control variable u_i as:

$$\left[P_i^{b,d}\ P_i^{b,c}\Delta P_i^{pcc,B}\bar{P}_i^{pcc,S}\Delta P_i^{pcc,S}\Delta P_i^{l,u}\Delta P_i^{l,l}\right]^T \quad (9)$$

Denoting with N the prediction and control horizon, let $Y = [y_{i+1} \dots y_{i+N}]^T$ be the vector of future outputs and $\hat{Y}$ the corresponding vector of predictions. Let also $U_f = [{u_{i+1}}^T \dots {u_{i+N}}^T]^T$ be the vector of future control actions, and $D = [d_{i+1} \dots d_{i+N}]^T$ the vector of (predicted) future disturbances in the microgrid where $d_{i+k} = [\bar{P}_{i+k}^l P_{i+k}^w]^T$, $\bar{P}_i^l$ being the expected load power and P_i^w the wind power. Then, one can express the output prediction as:

$$\hat{Y} = S_f U_f + S_{fd} D \quad (10)$$

where S_f and S_{fd} are suitable coefficient matrices.

As for wind power that is the main source of uncertainty for the control design problem, an ARIMA (2,1,1) model, tuned with the Recursive Maximum Likelihood (RML) method, has been used to forecast the wind speed over the short-term prediction horizon. Then, the wind speed predicted values have been converted into wind power values using an empirical speed-to-power curve. For medium-term (*i.e.*, day-ahead) power production, similar to (Teleke et al., 2010), the day-ahead power production (with respect to which the imbalance charges are calculated) is not actually estimated. Rather, the prediction process is emulated by artificially adding a white Gaussian noise to the exact production profile. Then, the generated prediction profile is subject to have 20% of prediction error.

4.2 MPC Formulation

As discussed in the following, the energy management problem can be formulated as a QP problem of the form:

$$\begin{gathered}\min\ J = {U_f}^T \mathrm{A} U_f + B U_f + C \\ \text{Subject to: } D U_f \leq b\end{gathered} \quad (11)$$

Note that expression of $b_m \leq DU_f \leq b_M$ and $DU_f \leq b_M$ and $-DU_f \leq -b_m$ are interchangeable.

The cost function includes several additive terms, that address different objectives:

$$J = w^R J^R + w^C J^C + w^I J^I + w^L J^L + w^F J^F \quad (12)$$

where w^R, w^C, w^I, w^L, and w^F, are weight coefficients and J^R, J^C, J^I, J^L, and J^F, are cost terms that account for battery power smoothing, economic benefit due to electricity trading, imbalance charges, load curtailment penalties, and control feasibility, respectively. All the terms in (6) are expressed as quadratic functions of the decision variables U_f. A detailed explanation of each of the mentioned terms together with hard constraints related to the operating conditions of the various components is given in the next sub-sections.

4.3 Cost Function Terms

In this section, the construction of each cost function term is introduced and it turns out that the expression of these terms falls into the quadratic form (11), upon observing that all related variables are either decision variables included in U_f or functions of U_f.

Battery Power Regularization (J^R)

The cost function term J^R enforces the smoothness of the battery power:

$$J^R = \sum_{k=i+1}^{i+N} (\Delta P_k^b)^2 \quad (13)$$

where ΔP_k^b denote the deviation between consecutive control moves regarding the battery charging and discharging.

$$\Delta P_k^b = P_k^b - P_{k-1}^b = P_k^{b,d} - P_k^{b,c} - P_{k-1}^{b,d} + \\ + P_{k-1}^{b,c} = \Delta P_k^{b,d} - \Delta P_k^{b,c} \tag{14}$$

Energy Cost Minimization (J^C)

This term accounts for the economic benefit resulting from electricity trading with the grid (disregarding monetary penalties):

$$J^C = J^{C,S} + J^{C,B} \tag{15}$$

where $J^{C,S}$ and $J^{C,B}$ account for the overall costs related to selling and buying energy, respectively. Notice that $J^{C,S}$ is a negative term that represent earning derived from selling electricity to the grid.

Imbalance Charges Minimization (J^I)

Penalties are inflicted if P_i^{pcc} exceeds the interval $\left[P_i^{pcc,SP} \pm \Delta P_i^{pcc,SP}\right]$ at time step i, where $P_i^{pcc,SP}$ and $\Delta P_i^{pcc,SP}$ are the reference power profile and its maximum allowed deviation, respectively. The power flow towards the grid is divided into a nominal component $(\bar{P}_i^{pcc,B} - \bar{P}_i^{pcc,S})$ and a deviation $\Delta P_i^{pcc,B} - \Delta P_i^{pcc,S}$. The nominal power is constrained to take values within the penalty bounds. On the other hand, an additional term J^I of the cost function introduces a soft constraint on the deviation from the boundaries $\Delta P_i^{pcc,S}$ as follows:

$$J^I = \sum_{k=i+1}^{i+N} \left(\Delta {P_k^{pcc,B}}^2 + \Delta {P_k^{pcc,S}}^2\right) \tag{16}$$

In this way, what is minimized is not the distance from the reference power, but that from the boundaries related to imbalance charges, thus allowing the system to exploit the full range allowed by the contract stipulated with the utility operator.

Load Curtailment Penalty (J^L)

To maximize the economic profit and reduce imbalance charges, the control system has also the option to modify the request from the load side within some flexibility bounds arranged with the user. Included in such arrangements is a penalty imposed for not fulfilling the load side demand. Let t^l and t^u be $1 \times N$ vectors representing the curtailment penalty tariffs over the prediction horizon (different tariffs are generally applied depending on the sign of the deviation with respect to the nominal load demand). In any case, the load side receives Then, the cost function term J^L is constructed as:

$$J^L = t^l \begin{bmatrix} \Delta P_{i+1}^{l,l} \\ \vdots \\ \Delta P_{i+N}^{l,l} \end{bmatrix} + t^u \begin{bmatrix} \Delta P_{i+1}^{l,u} \\ \vdots \\ \Delta P_{i+N}^{l,u} \end{bmatrix} \tag{17}$$

Feasibility Term (J^F)

In practice, only one control action regarding the charging and discharging variables is applicable at a given time. To ensure this property, a soft constraint is enforced by introducing an additional cost term related to feasibility which is minimal when at least one of the two equals zero:

$$J^F = \begin{bmatrix} P_{i+1}^{b,C} & P_{i+2}^{b,C} & \dots & P_{i+N}^{b,C} \end{bmatrix} \begin{bmatrix} P_{i+1}^{b,D} \\ \vdots \\ P_{i+N}^{b,D} \end{bmatrix} \tag{18}$$

4.4 MPC Constraints

This section presents the considered constraints. As with cost function terms, with suitable choices of the coefficient matrices, the constraints can be rewritten in the general form of linear inequalities as in (11).

Maximum Battery Power

Beside being non-negative, the ESS charging and discharging powers are also bounded by the maximum charging ($P_{max}^{b,C}$) and discharging power ($P_{max}^{b,D}$), respectively.

$$\begin{aligned} 0 \le {P_k}^{b,D} \le P_{max}^{b,D} \quad \forall k = i+1, \dots, i+N \\ 0 \le {P_k}^{b,C} \le P_{max}^{b,C} \quad \forall k = i+1, \dots, i+N \end{aligned} \tag{19}$$

Bounds on the state-of-charge

Constant charging and discharging efficiencies over the prediction horizon N have been employed to compute the constraints on the battery energy. Such constant efficiencies are computed as functions of the state of charge value at the previous step, $S\hat{O}C_i$:

$$SOC_{min}^b \le SOC_{k-1}^b + \begin{bmatrix} -\frac{1}{\bar{k}_D} & \bar{k}_C \end{bmatrix} \begin{bmatrix} P_k^{b,D} \\ P_k^{b,C} \end{bmatrix} T_s \\ \le SOC_{max}^b \\ \forall k = i+1, \dots, i+N \tag{20}$$

where SOC_{min}^b is the minimum capacity of the battery [%], SOC_{max}^b is the maximum capacity of the battery [%], $\bar{k}_D = \bar{\eta}_D(S\hat{O}C_i)C_b$ and $\bar{k}_C = \bar{\eta}_C(S\hat{O}C_i)/C_b$.

Sign of the Power Flow Terms at the PCC

As already discussed (see equations (3)-(5)), the purchase $\bar{P}^{pcc,B} + \Delta P^{pcc,B}$ and the sale $\bar{P}^{pcc,S} +$

$\Delta P^{pcc,S}$ components are both assumed non-negative.

$$\begin{aligned} 0 \le \bar{P}_k^{pcc,B} + \Delta P_k^{pcc,B} \quad \forall k = i+1, \dots, i+N \\ 0 \le \bar{P}_k^{pcc,S} + \Delta P_k^{pcc,S} \quad \forall k = i+1, \dots, i+N \end{aligned} \tag{21}$$

Allowed Range for the Power Flow at the PCC

As mentioned in *MPC formulation* section, the following hard constraint on the nominal power sold to the grid is applied:

$$\begin{aligned} P_k^{pcc,SP} - \Delta P_k^{pcc,SP} \le \bar{P}_k^{pcc,B} - \bar{P}_k^{pcc,S} \\ \le P_k^{pcc,SP} + \Delta P_k^{pcc,SP} \\ \forall k = i+1, \dots, i+N \end{aligned} \tag{22}$$

Load flexibility range

Given the upper and lower deviation terms from the load reference $\Delta P_i^{l,up}$ and $\Delta P_i^{l,low}$ defined for each time step i, the MPC computes the optimal solution according to the following constraints over all the prediction horizon:

$$\begin{aligned} P_k^{l,REF} - \Delta P_k^{l,low} \le P_k^l \le P_k^{l,REF} + \Delta P_k^{l,up} \\ \forall k = i+1, \dots, i+N \end{aligned} \tag{23}$$

where $P_i^{l,REF}$ is the nominal electrical power consumed by the load, i.e. the load demand.

5 SIMULATION RESULTS

A set of 3 experiments has been carried out to emphasize different aspects of the optimization problem on 5 different microgrid settings, with 10 different objective functions.

5.1 Scenarios and Experiments

Unless otherwise stated, the parameter values listed in Table 1 are adopted in all the simulations, where t^u, t^l, and t^{im} are the penalty tariffs related to curtailment penalties for excess energy, insufficient energy and imbalance charges, respectively, N and T_s are the parameters for the MPC execution (the prediction/control horizon and the sampling time, respectively), and ΔP^l is the level of load flexibility. Notice that, for simplicity, we assumed the imbalance charge tariff, the curtailment penalty tariff and the load flexibility range to be constant, although the presented approach remains valid even if those quantities are allowed to change over time. In this work, a typical load demand is studied with two peak consumption periods and the profile varies in hourly manner. Correspondingly, a typical daily electricity tariffs follows a similar trend as the load profile. Notice that the purchase tariff is always higher by 19€/MWh compared to the sale tariff.

To analyze the performances achievable by taking advantage of the load flexibility and by employing an ESS, we considered 5 different microgrid settings (listed as scenario S0 to S4 in Table 2).

Table 1: Simulation parameters.

Parameter	Unit	Value	Parameter	Unit	Value
$P_{max}^{b,D}$	MW	1	t^{im}	€/MWh	40
$P_{max}^{b,C}$	MW	1	t^u	€/MWh	90
SOC_{min}^b	[%]	20	t^l	€/MWh	90
SOC_{max}^b	[%]	100	N	-	20
C_b	MWh	5	T_s	min	15
ΔP^l	[%]	10			

Table 2: Microgrid scenarios.

Scenario	RES	Load flexibility	ESS
S0	NO	NO	NO
S1	YES	NO	NO
S2	YES	YES	NO
S3	YES	NO	YES
S4	YES	YES	YES

To represent the condition where the RES is not available (scenario S0), variable P_i^w is set to 0 for all i. Similarly, to model the absence of the ESS (scenarios S0, S1, and S2), we set $SOC_{min}^b = SOC_{max}^b = 0$. Finally, $\Delta P^l = 0\%$ in scenarios S0, S1, and S3, to account for the exact load following requirement. Notice that for scenarios S0 and S1 no actual control choice has to be taken (and therefore no optimization is carried out), since the load requirement must be exactly followed and there is no ESS to manage. In these cases, all the energy required by the load at each period must be provided by the grid (or the wind power generator). These scenarios are included for reference purposes only.

Regarding the cost function weights, a wide variety of combinations have been analyzed (see Table 3) to study the sensitivity of the control results to these tuning knobs. In all considered settings the control feasibility weight has been set to a high value ($w^F = 10^5$), as feasibility is a critical requirement of the system. Conversely, the battery power regularization term has been set to a small value ($w^R = 1$), since in this paper the focus is on the monetary optimization problem.

Various combinations of the other 3 weights (w^C, w^I and w^L) are introduced to emphasize different goals. More specifically, we can identify 3 specific goals, namely *Energy Profit* (EP), *Market*

Committment (MC), and *User Comfort* (UC). Notice that in the short-term simulation period (i.e., 2-month period) the capital and battery degradation costs are neglected for simplicity. The EP goal aims at maximizing the revenues resulting from purchasing/selling electricity from/back to the grid, and is achieved by setting a high value for w^C. MC is associated to the energy trading arrangements made with the utility. Consequently, minimizing the imbalance charges optimizes the MC (high w^I). Finally, UC is maximized if the load request is perfectly tracked by the control system. Therefore, it is pursued by reducing the load curtailment penalties (high w^L). For simplicity, goals EP, MC and UC have been discretized into 3 levels (low, medium, high), so that many combinations can be constructed to account to different overall objectives of the microgrid management.

Table 3: Cost function weight tunings.

Group	Weight	parameters					goals		
	tuning	w^R	w^C	w^I	w^L	w^F	EP	MC	UC
1	W1	1	1	1	2000	10^5	low	low	high
	W2	1	1	250	1	10^5	low	high	low
	W3	1	2000	1	1	10^5	high	low	low
2	W4	1	1	250	2000	10^5	low	high	high
	W5	1	2000	1	2000	10^5	high	low	high
	W6	1	2000	250	1	10^5	high	high	low
3	W7	1	250	10	2000	10^5	med	med	high
	W8	1	250	250	250	10^5	med	high	med
	W9	1	2000	10	250	10^5	high	med	med
4	W10	1	250	10	250	10^5	med	med	med

To represent the most significant combinations, the weight settings are aggregated in 4 different groups. Group 1 refers to mono-objective problems, while 2- and 3- objective cost functions are minimized in Groups 2 and 3, respectively. Notice, in particular, that for each case of Group 3 a high weight value is assigned to one of three goals while the remaining two are associated with medium weight values. Finally, Group 4 reports a balanced weighting designed to (approximately) minimize the overall cost.

The experiments performed are listed below:

1) Comparison between different scenarios
2) Role of the cost function weights
3) Impact of load flexibility

5.2 Experiment 1: Comparison between Different Scenarios

A 2-month long simulation has been carried out for all scenarios. Weight tuning W10 is employed, where appropriate (scenarios S2, S3, and S4). Table 4 presents the corresponding costs. Apparently, the use of the RES can reduce the total cost by an order of magnitude in the given settings (compare scenarios S1-S4 with S0). Notwithstanding the low round-trip efficiency of the battery (ratio of total energy discharged from ESS divided by total energy charged to ESS) and the inclusion of load curtailment penalties, scenario S4 provides the best total cost of the system with a 15.2% improvement over S3, a 24.3% improvement over S2 and 32.6% over S1. Negative entries in Table 4 represent earnings derived from selling electricity to the main grid.

Table 4: Results for Experiment 1.

Scenario	Total cost [€]	Curtailment penalty [€]	Imbalance charge [€]	Energy trading [€]
S0	359960	0	0	359960
S1	56722	0	38524	18197
S2	50569	22062	31343	-2836
S3	45065	0	25569	19496
S4	38231	22101	19151	-3021

5.3 Experiment 2: Cost Function Weights

This experiment is aimed at evaluating the behavior and performance of the control system for different combinations of the cost function weights (refer to Table 3), resulting in different levels of achievement regarding the mentioned EP, MC, and UC goals. All simulations refer to scenario S4. Results are reported in Table 5.

Table 5: Results for Experiment 2.

Weight tuning	Cost (€)			
	load curtailment	imbalance charges	electricity trading	total
W1	0	24940	20978	45918
W2	31023	17322	2288	50633
W3	32699	41907	-26198	48409
W4	16415	19556	9897	45868
W5	19005	43357	-15630	46733
W6	32069	17634	-4432	45271
W7	0	25709	19634	45342
W8	28063	17483	1408	46954
W9	32699	29576	-20908	41367
W10	22101	19151	-3021	38231

Notice that, if the system focuses only on UC (*e.g.*, W1), the curtailment penalty is 0 € as the load request is completely fulfilled. On the contrary, the imbalance charges are always greater than 0, because the power and energy limitations of the ESS, as well as the inevitable short-term prediction errors on the wind power production, do not always allow a tracking of the expected production profile within the acceptable tolerance levels.

5.4 Experiment 3: Load Flexibility

A further analysis has been carried out to ascertain the impact of the load flexibility level on the control performance. To this aim, parameter ΔP^l(i.e., level of load flexibility) is varied in the range 0 ÷ 10 % of the load demand. Actual short-term wind prediction is employed. Weight tuning W10 has been used for this analysis. The results are summarized in Table 6 that shows an improvement in the total cost and average electricity cost when increasing the load flexibility. Load shedding during peak hours is an obvious reason for this improvement.

Table 6: Effects of load flexibility.

Load flexibility range [%]	Total cost [€]	Provided/expected energy [%]	Rate [€/MWh]
0	45065	100.00	12.40
2	43585	98.61	12.17
4	42120	97.26	11.92
6	40598	95.96	11.64
8	39390	94.68	11.45
10	38231	93.45	11.26

The load flexibility appears to play a role similar to the ESS in rebalancing the energy in the system, by increasing or decreasing the load profile, in order to reduce the imbalance charges and the energy trading cost. The larger the load flexibility level, the greater the possibilities to enact load shedding and energy balancing strategies in the system. A 17.9% difference in terms of the total cost is observed between the worst (*i.e.*, 0% load flexibility) and the best case (10% load flexibility).

6 CONCLUSIONS

In this paper, a model predictive control approach to the optimal energy management and control in microgrids is proposed, considering ESS (batteries), RES (wind farms), smart flexibile buildings and a connection to the main grid. A comprehensive and unified modelling framework is proposed to deal with realistic battery models, power tracking, imbalance charges, curtailment penalties, wind power prediction, under different objectives, operational constraints and scenarios. In particular, the paper shows how the proposed unified framework can address completely different scenarios (*e.g.*, with or without RES, ESS, and load flexibility), and demonstrates how different optimization objectives can be pursued by manipulating specific design parameters.

Future research directions will include the improvement of the prediction of the RES production, since this appears to be a major factor that influences the overall performance, and the automatic setting of the MPC main parameters (namely the cost function weights). Furthermore, the same comprehensive approach discussed here will be extended to a distributed scenario, with multiple loads, ESS's and RES's, in a distributed MPC framework.

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