A Two-layer Model Predictive Control based secondary control with economic performance tracking for islanded microgrids

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***Abstract*—This paper proposes a two-layer microgrid supervisor based on Model Predictive Control (MPC). The supervisor in the upper layer relies on an economical optimization that considers the cost of energy and the load and production forecasts to define the State of Charge (SoC) targets for each storage device on a timescale of 15 minutes. The lower layer displays a shorter timescale and aims to control the equipment to ensure the stability of the overall system and SoC tracking while satisfying the economic constraints specified by the upper layer. These two layers require an uniformization of the timestep and of the references in order to behave properly. The main contributions of this paper are the microgrid network modelling embedded in the optimization routine of the lower layer and a discretization for integrating upper-layer references.**

***Index Terms*—Microgrids, Predictive Control, Hierarchical control, Energy Management System, Power Management System**

I. INTRODUCTION

Hierarchical control structure is commonplace in the scientific and industrial communities for microgrid control. It has been studied for a long time since the renewal of the microgrid concept [1]. It was first a mimic of control levels of conventional power systems and of ancillary services [2]. It was also convenient in such a way that higher-level layer could consider and optimize the stochastic nature of the renewable production in an offline optimization routine without altering the system stability by the increase of computational burden. However, it only optimizes the economic operation of the microgrid. Thus, a second layer is needed to handle the technical supervisor of the microgrid. For this layer, several control techniques may be applied such as fuzzy logic in [3] in which the author developed rules-based supervisor to define the power references. Another technique exploits an optimization routine and a prediction model named Model Predictive Control in [4]. The MPC technique allows to handle multiple states and inputs when the model is well known and in presence of accurate forecasts, which is the case for microgrid dynamics.

Most of the literature on multi-source power cells focus mainly on an accurate modeling of the dynamics of every equipment and aims to optimize an economic criterion based on operational cost, CO2 emissions. For example, in [4], a performance index is defined as a combination of the different costs and the output powers. However, this literature generally ignores the fact that in real life, microgrids encompasses lines, loads and low-level controller which contribution cannot be neglected in the overall model. Along with the purpose of alleviating the computational burden, a multi-layer hierarchical control is preferred to a centralized supervisor when applied to microgrids. In addition, the microgrid system embeds distributed local controllers such as droop control to preserve stability that must be used as lever. Such a multi-layer supervisor of a grid-connected microgrid control is proposed in [5], in which the upper layer computes the daily exchange with the grid, and an intermediate layer translates these daily references into real time values for two clusters with similar equipment. By doing so, Cominesi et al. reduce the computational burden but require an additional central supervisor for each cluster to deal with the diversity between the assets within a single cluster. In [6], the same authors improved the hierarchical control by adding a stochastic MPC to a daily economic planning to minimize the discrepancies due to the stochastic resources. The use of the shrinking horizon MPC at the lower layer allow to integrate the dynamics of the assets and the complete model is probabilistic in its nature, so are the constraints. A similar approach has been proposed in [7] in which the upper layer aims to mitigate the severe fluctuations and the lower layer to keep constant the output power.

However, in these publications, the embedded model in the fast supervisor is the same as that displayed in the upper-layer or neglect the impact of the microgrid network. Moreover, both layers are assumed to be synchronous and consider a shrinking horizon to handle the upper layer references, whereas the timescale of the layers in the actual supervisors are not the same. Different multi-layer MPC architectures have been compared in [8], one with a steady state optimization and a target correction at the lower layer side that can handle an additional task (Figure 1 (a)), a global nonlinear MPC (Figure 1 (b)) and a dynamic real-time optimizer with a tracking controller (Figure 1 (c)).

To address the issues previously pointed out, we propose an improved two-layer supervisor combining the advantages of the first architecture with the tracking controller depicted in the third architecture. Throughout the paper, the upper layer is referred to as EMS, and the lower as PMS, standing respectively for Energy Management System and Power Management System. Our supervisor embeds an economic optimization at the upper level, based on a classical modeling of the microgrid, and a trajectory tracking problem at the lower level. This optimization algorithm embeds a refined model of the network which is able to handle and anticipate the voltage and frequency variations and takes the dynamics of the grid into account.

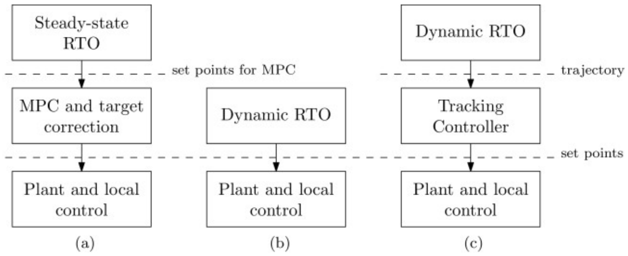

Figure 1: Multi layer architecture as proposed in [8]

The rest of this paper is organized as follows. In section II, the components and network models with the corresponding assumptions are detailed. The third section presents different strategies to embed the economic constraints in the lower layer. Finally, the last part displays the simulation results of the proposed strategy.

II. Predictive microgrid controller

It has been chosen to develop a discrete MPC for the PMS. The sampling time is set to 1 minute and the horizon control to 15 minutes which matches one upper layer timestep. Model Predictive Control has been widely used in the control engineering community [9]. The synoptics of this technique is shown in Figure 2 and it exhibits several advantages:

i) Design of a prediction model to accurately handle system future behavior,
ii) ability to handle multiple dynamics,
iii) minimization of a multi-objective cost function while respecting constraints.

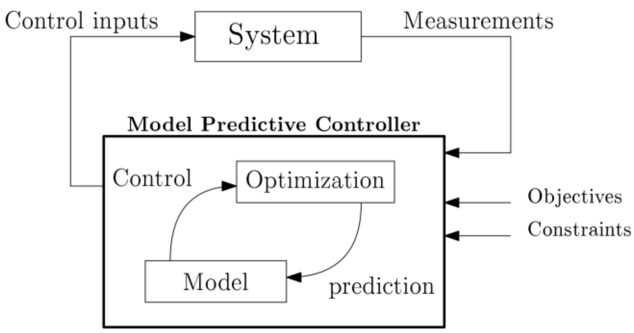

Figure 2: Model Predictive Controller synoptic

A. Controller objectives

Ideally, the lower layer controller can reach the nominal state according to the references and keep it along the timestep. Due to the stochastic nature of the production and consumption that prevail in the microgrid, the upper layer only considers the global energy over the whole timestep (or constant power over a fixed timestep) and the evolution of the States of Charge. Our first objective is then to track the predicted states of charge coping with the production and load fluctuations. The levers to meet these objectives are the output powers references which are sent to the controlled equipment: storage devices, diesel generator. A second objective is to minimize the changes of references. The objective function of the microgrid supervisor is formulated as:

$$\min_{\Delta u} J = \sum_{k=1}^{Nc} \left[\alpha \left(x(k) - x^*(k) \right)^2 + \beta \left(\Delta u(k) \right)^2 \right] \quad (1)$$

Where the first term represents the error between the SoC targets and the SoC reached by the lower layer, $\tilde{x}(k)$ and $x^*(k)$ are the predicted and reference state for timestep k and the second minimize the effort of the levers. In this formulation, the control horizon N_c is equal to the prediction horizon.

B. Component modeling

1) Storage devices

The State of Charge dynamics for the battery can be modelled by the following discrete time state equations:

$$SoC(k+1) = \begin{cases} SoC(k) - \eta_{ch} \dfrac{P_b(k+1).Ts}{60}, P_b(k+1) < 0 \\ SoC(k) - \eta_{disch} \dfrac{P_b(k+1).Ts}{60}, P_b(k+1) > 0 \end{cases} \quad (2)$$

Subject to: $\underline{SoC} < SoC(k+1) < \overline{SoC}$

$$\underline{P_b} < P_b(k+1) < \overline{P_b}$$

where η_{ch} and η_{dis} are the charging and discharging efficiencies of the battery, P_b the output power, T_s the sampling time and $\overline{X}$ and $\underline{X}$, are the maximum and minimum bounds of the variable X.

2) Grid forming inverter

A grid forming inverter is a power electronic interface that can create and maintain the characteristics of a power system, that are voltage and frequency. This converter is mainly used along with storage devices or coupled renewable-storage. It can be modeled by the following equations representing the droop control:

$$\begin{cases} \omega(k+1) - \omega^* + k_p \Delta P = 0 \\ V(k+1) - V^* + k_q \Delta Q = 0 \end{cases} \quad (3)$$

where u and ω are the output voltage and pulsation resp., and the superscript * denotes the reference values, k_p and k_q are the active and reactive droop coefficients resp.

In most of the grid codes, the reactive production of the converters is constrained to a predefined regulation such as Q(u) or tan(φ). For islanded microgrids, such regulations may not be applied, and the coordination of reactive power driven by the optimal supervisor. In the rest of this paper, we assume that inverters are only limited by the apparent output power:

$$\sqrt{P^2+Q^2} < S_{\max} \tag{4}$$

3) Diesel generators

The diesel generators are modelled as controlled output power sources with the following constraint:

$$\underline{P_{gen}} < P_{gen}(k+1) < \overline{P_{gen}} \tag{5}$$

The generator is also constrained by a minimal ON and OFF period. For the PMS prediction horizon, the state constraints are determined by the EMS output. In case of infeasibility, this is the only lever available and we remove these constraints and the cost and constraints are updated accordingly.

4) Renewable sources

The renewable energy resources are modelled as uncontrolled but predictable output powers. For the sake of simplicity, forecasts are assumed known for each time step over the prediction horizon.

C. Microgrid network and load modeling

The active and reactive power flow from node i to node k are defined by the following equations [10]:

$$P_i^{gen} - P_i^{load} = \sum_{j=1}^{N} |Y_{ij}||V_j||V_i|\cos(\delta_i - \delta_j - \theta_{ij})$$
$$Q_i^{gen} - Q_i^{load} = \sum_{j=1}^{N} |Y_{ij}||V_j||V_i|\sin(\delta_i - \delta_j - \theta_{ij})$$

In which, $|V_i|$, $|V_j|$, δ_i, δ_j are the voltage magnitude and angle resp., $|Y_{ij}|$ and θ_{ij} are the admittance matrix magnitude and angle resp. The power flow equations are nonlinear. In order not to increase the computation burden and by assuming that the disturbances are small, the model is linearized:

$$\Delta P_i = \frac{dP_i}{\partial V}\Delta V + \frac{dP_i}{\partial \delta}\Delta\delta + \frac{dP_i}{\partial \omega}\Delta\omega$$
$$\Delta Q_i = \frac{dQ_i}{\partial V}\Delta V + \frac{dQ_i}{\partial \delta}\Delta\delta + \frac{dQ_i}{\partial \omega}\Delta\omega$$

The compact discrete model of the network is as follows:

$$\begin{bmatrix} \Delta V_1(k+1) \\ \vdots \\ \Delta V_i(k+1) \\ \Delta\delta_2(k+1) \\ \vdots \\ \Delta\delta_i(k+1) \\ \Delta\omega(k+1) \end{bmatrix} = \begin{bmatrix} \frac{\partial P_i}{dV} & \frac{\partial P_i}{d\delta} & \frac{\partial P_i}{d\omega} \\ \frac{\partial Q_i}{dV} & \frac{\partial Q_i}{d\delta} & \frac{\partial Q_i}{d\omega} \end{bmatrix}^{-1} \begin{bmatrix} \Delta P_1^*(k) \\ \vdots \\ \Delta P_i^*(k) \\ \Delta Q_1^*(k) \\ \vdots \\ \Delta Q_i^*(k) \end{bmatrix} \tag{6}$$

and thus,

$$\begin{cases} V_i(k+1) = V_i(k) + \Delta V_i(k) \\ \omega_i(k+1) = \omega_i(k) + \Delta\omega_i(k) \\ \delta_i(k+1) = \delta_i(k) + \Delta\delta_i(k) \end{cases} \tag{7}$$

The Jacobian is updated with each new reference from the upper-layer. It is assumed constant for the routine of the lower-layer.

The voltage and frequency deviations are constrained to 5 % and 10% respectively.

$$\begin{cases} 0.95 < \omega(k+1) < 1.05 \\ 0.9 < V_i(k+1) < 1.1 \end{cases} \tag{8}$$

D. Global supervisor model

Finally, the supervisor answers the following optimization problem:

$$\min_{\Delta u} J = \sum_{k=1}^{Nc} \left[\alpha\left(x(k) - x^*(k)\right)^2 + \beta\left(\Delta u(k)\right)^2 \right] \tag{9}$$

subject to (2)-(8)

III. INTERLAYER STRATEGIES

As for many microgrid supervisor, the upper layer defines optimal operating point according to an economical optimization routine. However, these references need to be discretized in order to be embedded into a faster controller that predict the electrotechnical behavior of the microgrid, neglected in the upper layer.

A conventional shrinking-horizon MPC is illustrated in Figure 3, in which the EMS reference is kept constant during all the EMS timestep. One of the advantages to use a receding horizon and a discretization algorithm appears clearly from Figure 3 (b). Any disturbance at the end of the timestep will force the supervisor to degrade its performances to reach the set points in one lower layer timestep.

A straightforward strategy consists of an integral control of the error between the lower layer tracking and the interpolated upper layer references. Figure 4 (a) and (b) display two strategies with a discretization of the optimal economic set points, using a step shape and a linear interpolation. In the first one, the references are kept constant for the coming PMS time step. In the later, a linear interpolation of the EMS references defines the trajectory (Figure 4 (b)). This kind of discretization among others are already studied in [11], however, in this paper, the faster layer uses a shrinking horizon and the models are not that different as the ones used in microgrid supervisors.

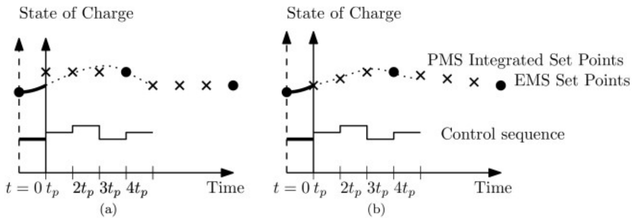

Figure 3: Conventional stair-based shrinking MPC supervisor (a) initial state of the system and control sequence – (b) control sequence and predicted trajectory at t= t_p

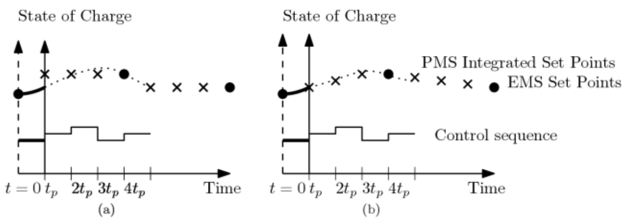

Figure 4: Proposed strategies - (a) with constant references - (b) with linear interpolated references

Finally, the general algorithm to interface both layers is shown in Algorithm 1. It consists of the calculation of the next two EMS references and a projection on to the faster timestep to define the PMS trajectory that are integrated into the objective function.

IV. Simulation Results

The proposed supervisor has been implemented in MATLAB with the toolbox YALMIP [12].

Five-second real measurement data for photovoltaic and ten-minute load profile are used in these simulations. The forecast provided to the supervisor is a one-minute average of the measurement introducing fluctuations. The simulations are performed with microgrid as shown in Figure 5.

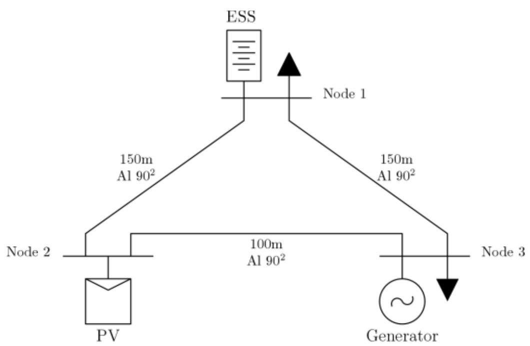

Figure 5: Microgrid test bench configuration and topology

The flowchart of the proposed supervisor is depicted in Figure 10. At first, the economical references are obtained from the EMS module. Figure 6 shows the output of the receding horizon-based EMS with the load and PV production as parameters. The graph at the bottom shows the optimal trajectory of the SoC that is used as reference in the PMS. From this layer it can be observed that the battery will not only be recharged by the PV production, but also by the generator set that need to be started up several time during the two days. By doing so, the state of charge of the battery will remains within its limitations (0.2-1 p.u).

The next step is dedicated to the discretization of the economical trajectory and to the construction of the prediction model based on a Newton-Raphson-based power flow algorithm. Finally, the prediction module is updated, and the MPC-based supervisor defines the optimal changes of references for the actuator.

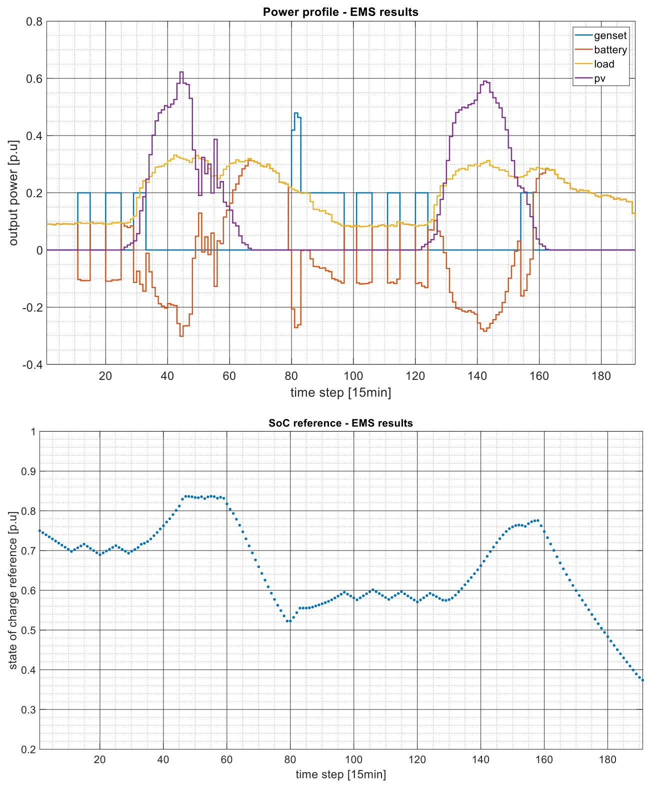

Figure 6: Energy management results – top: power profiles, bottom: state of charge references

Figure 7 displays the results of the proposed supervisor, the power profile and State of charge tracking for two consecutive days. By comparing the PV production for both layers, it is worth focusing on the compensation of fast fluctuation of the photovoltaic production by adjusting the output power of the batterie. Still, no significative effect induces a change in power references, and the PMS let the droop controller adjust the required power. This results in the voltage and frequency deviation shown in Figure 9. Different parameters and coefficients to more penalize the state of charge deviation could lead the supervisor to change the power references in case of larger SoC or frequency or voltage deviations. The node voltages and frequency remain within the boundaries with a maximal deviation of 0.018 p.u and 0.023 p.u respectively.

Figure 8 displays the comparison between the expected output power from the EMS, and the actual output power of the PMS layer (top) and the comparison between SoC reference and real SoC (bottom). It can be noticed that the proposed supervisor is able to track the reference with an error less that a percent while maintaining the system stable and during fast changes in the forecasts.

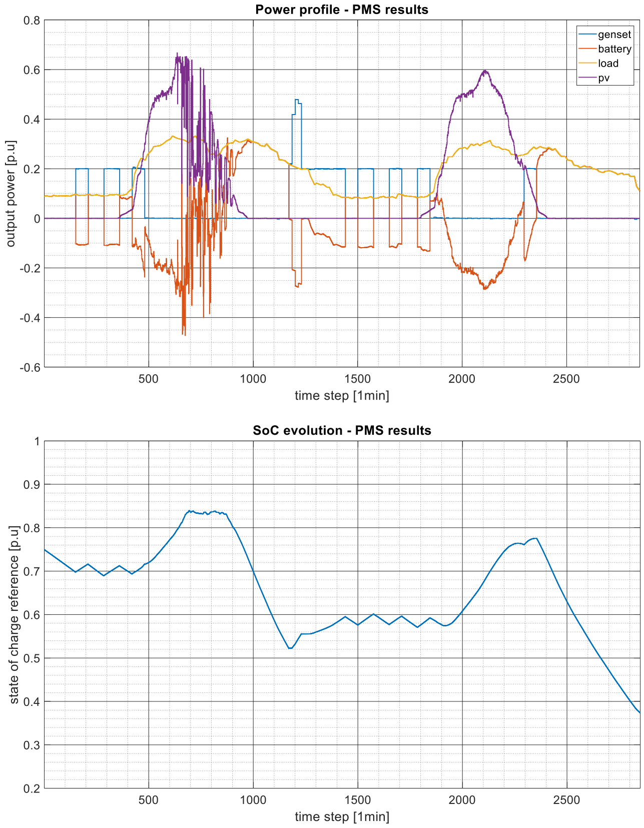

Figure 7: Power management results – top: power profiles, bottom: state of charge tracking

Finally, comparing these figures for the two different days simulated, one with an accurate forecast, and the other with fast fluctuation, it can be observed that the system is subject to significative disturbances even with a simple microgrid network. This highlights the interest of an intermediate layer that deals with the network characteristics for more and more complex microgrid topologies.

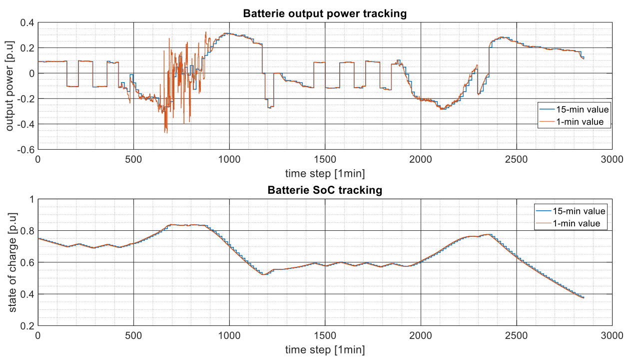

Figure 8: EMS (blue line) – PMS (red line) Comparison – top: batterie output power, bottom: State of charge

V. CONCLUSION

This paper proposes a novel supervisor for real time management of an islanded microgrid. This supervisor is based on a receding horizon two-layer Model Predictive Controller that embeds a long-term economic optimization and a faster dynamic tracking MPC. The latter layer aims to tracks the economic performance predicted while maintaining voltage and frequency stability within the microgrid. For this purpose, a discrete linearized model of the network and of the equipment is included. Simulations outlined the effectiveness of such a supervisor to track the economical references.

Further works will focus on two different aspects. The first one is handling severe disturbances such as a loss of production or predictive model taking into account physical model of the microgrid. In contrast with classical microgrid model, the proposed supervisor would be able to figure out precisely and in real time, the energy margin to interact with different microgrids connected through a MV or LV network to provide ancillary services and emergency responses to global network disturbances.

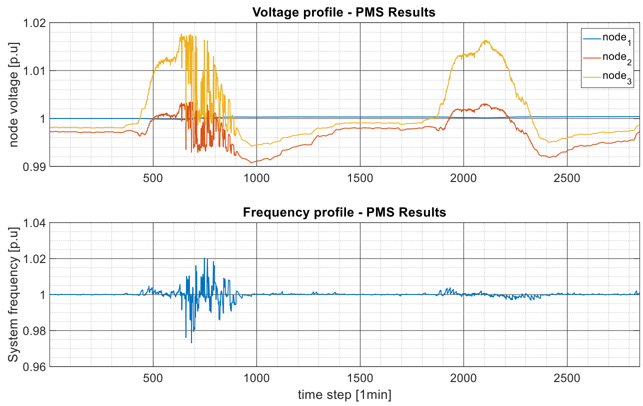

Figure 9: Top: node voltage profile, bottom: frequency profile

REFERENCES

[1] J. M. Guerrero, M. Chandorkar, T. Lee, and P. C. Loh, "Advanced Control Architectures for Intelligent Microgrids; Part I: Decentralized and Hierarchical Control," *Industrial Electronics, IEEE Transactions on*, vol. 60, no. 4, pp. 1254–1262, 2013.

[2] T. L. Vandoorn, J. C. Vasquez, J. De Kooning, J. M. Guerrero, and L. Vandevelde, "Microgrids: Hierarchical control and an overview of the control and reserve management strategies," *IEEE Industrial Electronics Magazine*, vol. 7, no. 4, pp. 42–55, 2013.

[3] B. Robyns, A. Davigny, and C. Saudemont, "Methodologies for supervision of Hybrid Energy Sources based on Storage Systems - A survey," *Mathematics and Computers in Simulation*, vol. 91, pp. 52–71, 2013.

[4] J.-Y. Dieulot, F. Colas, L. Chalal, and G. Dauphin-Tanguy, "Economic supervisory predictive control of a hybrid power generation plant," *Electric Power Systems Research*, vol. 127, pp. 221–229, 2015.

[5] S. R. Cominesi, A. La Bella, M. Farina, and R. Scattolini, "A multi-layer control scheme for microgrid energy management," *IFAC-PapersOnLine*, vol. 49, no. 27, pp. 256–261, 2016.

[6] S. Raimondi Cominesi, M. Farina, L. Giulioni, B. Picasso, and R. Scattolini, "Two-layer predictive control of a micro-grid including stochastic energy sources," in *2015 American Control Conference (ACC)*, 2015, pp. 918–923.

[7] D. Zhu, R. Yang, and G. Hug-Glanzmann, "Managing microgrids with intermittent resources: A two-layer multi-step optimal control approach," in *North American Power Symposium 2010*, 2010, pp. 1–8.

[8] L. Würth, R. Hannemann, and W. Marquardt, "A two-layer architecture for economically optimal process control and operation," *Journal of Process Control*, vol. 21, no. 3, pp. 311–321, 2011.

[9] S. J. Qin and T. A. Badgwell, "A survey of industrial model predictive

control technology," *Control Engineering Practice*, vol. 11, no. 7, pp. 733–764, Jul. 2003.
[10] P. Kundur, *Power system control and stability*. New York: McGraw, 1994.
[11] A. Abreu, R. Bourdais, and H. Guéguen, "Inter-Layer Interactions in Hierarchical MPC for Building Energy Management Systems," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 12027–12032, Jul. 2017.
[12] J. Lofberg, "YALMIP : a toolbox for modeling and optimization in MATLAB," in 2004 IEEE International Conference on Robotics and Automation, 2004, pp. 284–289.

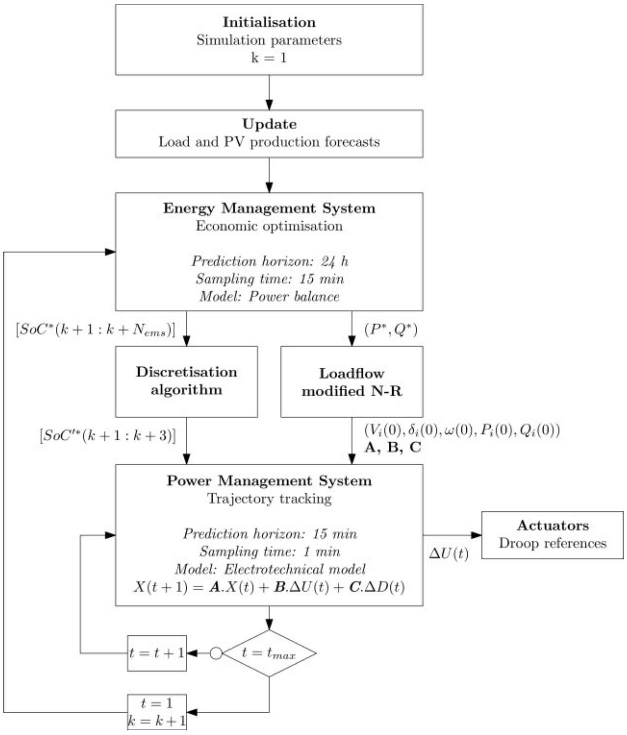

Figure 10: Flowchart of the proposed supervisor, from economic optimisation to actuators droop references

APPENDIX

A. Model development

1) Droop controlled inverters

$$P_i^{gen}(k+1) = P_i^{gen}(k) - K_p\left(\omega(k+1) - \omega^*\right)$$
$$Q_i^{gen}(k+1) = Q_i^{gen}(k) - K_q\left(V_i(k+1) - V^*\right)$$

2) Diesel generator

$$P_i^{gen}(k+1) = P_i^{gen\_ref}(k) + \Delta P_i^{gen}(k)$$
$$Q_i^{gen}(k+1) = Q_i^{gen\_ref}(k) + \Delta Q_i^{gen}(k)$$

3) Battery model

$$SoC(k+1) = SoC(k) - \eta\frac{\Delta t}{60.C}P_i^{gen}(k+1)$$
$$SoC(k+1) = SoC(k) - \eta\frac{\Delta t}{60.C}\Big[P_i^{gen}(k)$$
$$-K_p\left(\omega(k+1) - \omega^*\right) + \Delta P_i^{gen}(k)\Big]$$

B. Simulation parameters

P_{base} (kW)	100
SoC_{base} (kWh)	500
$P_{max} - P_{min}$ (p.u)	1 – (-1)
$SoC_{max} - SoC_{min}$ (p.u)	1 – 0.2
ΔU (p.u)	0.1
Δf (p.u)	0.05
S_{max} (p.u)	1.06

C. Integration algorithm

ALGORITHM

Initialization
Update microgrid measurements and model,
$t_e = \alpha t_p$,
$t = 1$,
Routine

1. Collect economic set points
2. For the next PMS control horizon,
   if t mod $t_e = 0$, update EMS interpolated set points.
   1.1. Make the discretization for each EMS timeslot considered,
   1.2. Update the PMS energy trajectory.
3. Solve MPC routine
4. Apply control sequence
5. $t = t + 1$

Algorithm 1: Integration of economic set points into microgrid supervisor