Real-time Cost Optimisation for Power Management in Microgrids Using Multi-Agent Control

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***Abstract*— This paper presents the application of Multi-Agent systems with model predictive control for an AC microgrid, implementing real-time generation cost minimisation. The Multi-Agent control is tested against heuristic optimisation methods. It is shown that the control can reduce costs without the need of a central controller and in times of the order of milliseconds, making online optimisation possible. A test microgrid and the primary control were simulated in an OPAL-RT while the secondary control developed in Java manages the system over TCP/IP.**

Keywords — *Power Management, Multi-Agent, Decentralised control, AC Microgrid*.

I. Introduction

The concept of a microgrid as a building block of the smart grid has appeared in recent years to improve the conventional model of energy transmission in terms of reliability, demand side management and flexibility [1]. A microgrid is a collection of distributed generation units (DGUs) and loads, connected to the grid in a point of common coupling (PCC) at the physical layer, witch a regulation system at the communication layer.

The control of a microgrid is done in a hierarchical way of 3 levels, which stems from ISA-95, which allows the implementation of additional grid services [2–4]. The first layer of control is the primary control which directly controls each power source and has the highest time response. The second layer aggregates several primary controls of the same microgrid to coordinate them. This layer can be centralised or decentralised or have elements of both [2, 4]. The tertiary control deals with control at the distribution system level, to offer services between the grid and the microgrid or other microgrids. The control hierarchy is illustrated in Fig. 1.

Some of the current challenges for research in microgrid control are the improvement of stability, expandability and cost effectiveness[5]. To address these, this paper proposes a controller that allows a reduction in cost of generation by improving the capacity of the secondary control to find the minimum in the power cost function, while the voltage and frequency remain stable in the primary control. The control is based on Multi-Agent System (MAS) in combination with Model Predictive Control, which also allow flexibility in the control with the microgrid.

The rest of the paper is organised as follows: Sections II and III describe the control hierarchy and control methods used, the proposed controller and the optimisation problem for the secondary control. In section IV, a microgrid case study is presented with 3 load scenarios for power management, the real-time simulation model is discussed, which is used to test the capacity of the MAS to respond in real-time, followed by the results in terms of cost minimisation and voltage and frequency response of the simulation in section V. Finally, conclusions are presented to summarise the current state of the power management control.

II. Hierarchical Control

A. Primary control

Most primary controllers use two control loops to regulate the voltage and current of the DGU. The primary control of [6] is an example of a control with an inner and outer control loop, where the outer loop sends a reference for the inner loop, making a more stable, accurate and fast control. The most common communication-less decentralised control is the droop control [7], however it can not simultaneously offer good voltage regulation and power sharing, having to trade-off one for the other [5].

B. Secondary control

This control mainly optimises the use of DGUs in the microgrid, normally in terms of cost, however, optimising only for the cost of distributed generation may neglect other aspects such as reliability and flexibility, which compromise the operation of the distributed resources and the supply of energy [2] [8]. From [9] is worth noting the consideration of a room's air temperature as part of the Energy Storage System (ESS), in [10] the decay of the battery is considered and in [11] the use of renewables is also part of the objective function. The main optimisation tools are based on convex programming, dynamic

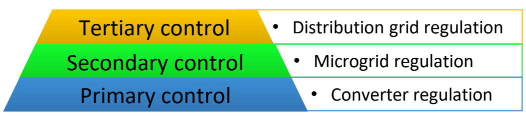

Fig. 1. Hierarchical Control.

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programming, stochastic programming, robust programming, and heuristic methods [1].

In the energy management system of [12], the effects of the time horizon and errors in the weather forecast are assessed in terms of total cost using GAMS. For improved reliability, [13] present distributed controls that maintain operation when a component disconnects.

1) Multi-Agent System: Most of distributed controls apply MAS, that can be briefly described as a system composed of individual intelligent units called agents that interact with each other in order to achieve multiple global and local objectives, either by cooperation or competition [2, 14]. Event-triggered agents are more efficient than State-dependent agents, as some agents may not need to be updated at the same rate as others in the system [15], State-dependent agents heavily rely on high frequency communication [16].

MAS can be applied to manage natural resources [17], a microgrid [18] or a combination of microgrids [19], where each agent has control over a DGU, loads, grid connection or aggregators [20]. Plug-and-play design of MAS ensures that any component can be added or removed at any point in the system without re-engineering the controls [21, 22]. Agents need to act coordinately, either by consensus to carry on most of their actions [23], or by following a leader agent [24–26].

2) Model predictive control: Model predictive control (MPC), also known as Receding Horizon control, is a control method where the plant is simulated to calculate its state in the future to select the control inputs required to reach such state [27]. MPC requires that all system outputs be measured with the same sample rate, this could be expensive if different parts of the system respond with dynamics of different time scales [28]. In explicit MPC the optimisation of the plant is done offline, and the controller works by looking up the required action in a table, which greatly reduces the amount of calculations necessary to obtain the system's forecast [29].

III. Proposed controller

A. Primary controller

The primary controller of each DGU is composed of an inner loop for voltage control and an outer loop for power control. For the inner loop a voltage amplitude and phase angle reference are used. Park's Transform, (1) and (2), is applied using a local clock ωt for PI control regulation of voltage signals, which outputs the signal reference for the converters. The outer loop is used to command the DGU to send or receive an specific amount of active and reactive power, given the power references. The main difference from the droop control in [7], is that this method doesn't use the frequency for power regulation.The control diagram is ilustrated in Fig. 2.

$$V_{dq0} = TV_{abc} \tag{1}$$

$$T = \begin{bmatrix} sin(\omega t) & sin(\omega t - \frac{2\pi}{3}) & sin(\omega t + \frac{2\pi}{3}) \\ cos(\omega t) & cos(\omega t - \frac{2\pi}{3}) & cos(\omega t + \frac{2\pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \tag{2}$$

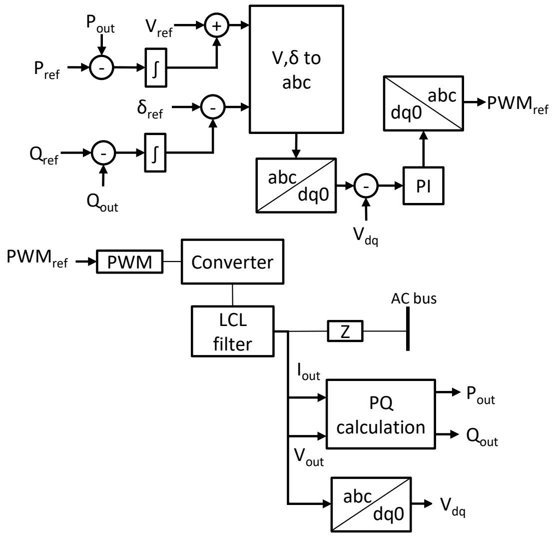

Fig. 2. The microgrid primary control

The primary control follows the equations of power flow between two buses in a short line model based on the lines of the distribution system, where the $\frac{X}{R} < 1$, decoupling active and reactive power in voltage amplitude and voltage phase angle control expressed by the following equations:

$$S = 3V_{s\phi}\Big(\frac{V_{s\phi} - V_{r\phi}\angle\delta}{Z}\Big)^* \tag{3}$$

$$S_s = P_s + jQ_s \approx 3(\frac{V_{s\phi}^2 - V_{s\phi}V_{r\phi}cos\delta}{R} + j\frac{V_{s\phi}V_{r\phi}sin\delta}{R}) \tag{4}$$

Where S_s is the apparent power sent, P_s is the active power sent, Q_s reactive power sent, V_s sending bus voltage, V_r receiving bus voltage, δ phase angle, R is the resistance of the line, Z is the impedance of the line and ϕ represents each phase. The instantaneous active and reactive power are calculated with all the phase current and voltages and feedback in the outer loop with (5) and (6):

$$p_{out} = (v_a i_a + v_b i_b + v_c i_c) \tag{5}$$

$$q_{out} = \frac{1}{\sqrt{3}}[(v_b - v_c)i_a + (v_c - v_a)i_b + (v_a - v_b)i_c] \tag{6}$$

B. Power optimisation

To maximise the economic benefits of using DGUs in a microgrid the total cost of the energy used by the microgrid must be minimised. One approach to this problem is optimising the power schedule for every DGU. The problem of optimal power schedule for all sources at every time segment is stated as follows:

$$\min \quad \sum_i \sum_j f_j((P_j(i)), \forall j \in K \wedge \forall i \in N \tag{7a}$$

$$\text{s.t.} \quad P_{jmin} \leq P_j \leq P_{jmax}, \tag{7b}$$

$$L - G = 0, \tag{7c}$$

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{7d}$$

Where j is each source in the set K of total number of sources, i represents each time segment in the set N of total time segments, f_j is the cost function of source j, and $P_j(i)$ is the power from source j at time i, P_{jmin} is the minimum power generation and P_{jmax} is the maximum generation from each source. SOC is state of charge of the ESS. SOC_{min} is the minimum charge and SOC_{max} is the maximum charge.

The second constraint of the problem refers to the balance of the power supply and demand, where the load L and generation G are defined as vectors where each element is total load and total generation at every time segment, respectively. Power to the grid is considered positive and power from the grid negative.

The third constraint is related to the SOC dynamic behaviour, setting a limit in how much power can be transferred continuously. To represent this a vector named SOC, containing the SOC at each time segment i is constructed, defining each element as:

$$SOC_{i+1} = SOC_i - \eta P(i), \forall i \in N \tag{8}$$

The next SOC element depends on the previous one and the power $P(i)$ sent or received by the ESS at each time i, multiplied by a constant η, related to the efficiency and capacity of charge and discharge. An initial SOC is defined as SOC_0. Equation (9) is equivalent to (7d) of the optimisation constraints and its evaluated element-wise.

$$\begin{aligned} &\left| SOC - \frac{SOC_{max} + SOCmin}{2} \right| - \\ &\frac{SOC_{max} - SOC_{min}}{2} \leq 0 \end{aligned} \tag{9}$$

The cost functions f_j from [10], are set as:

$$\begin{aligned} f_j(P_j(i)) = \begin{cases} b_j P_j(i) + c_j & P_j(i) \neq 0 \\ 0 & P_j(i) = 0 \end{cases}, \\ \forall j \in K \wedge \forall i \in N \end{aligned} \tag{10}$$

Where b_j and c_j are constants specific for each source j.

C. MAS Distributed control

The optimisation problem is solved with the MAS architecture at the secondary control, each agent has a set of communication and calculation behaviours, cycled every 10 milliseconds, this include sending and receiving agent communication language (ACL) messages from and to other agents and communication with the primary controller over TCP/IP.

Four types of agents where programmed in Java using the Java Agent Development (JADE) framework, the generator agents that control dispatchable DGUs, the ESS agent, the grid price agent and the load agent that informs other agents about the electricity price and the demand, together, they set the power and cost constraint for the cost minimisation. There is also an Agent Manager that creates and kills all other agents, and the Directory Facilitator (DF) Agent that allows the formation of the communication network of the other agents. These last two types of agents are in all JADE platforms, which contains all agents.

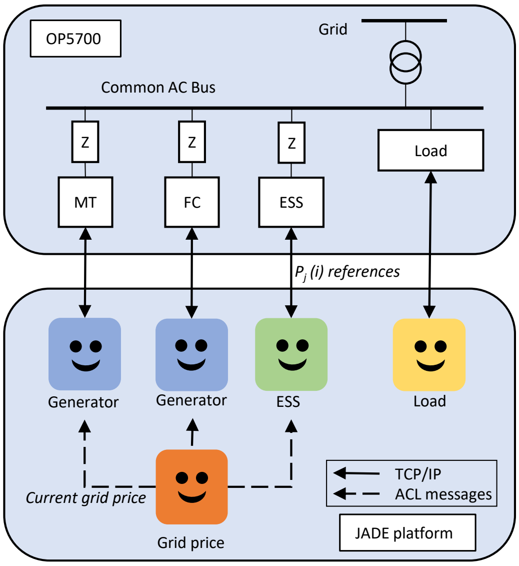

Fig. 3. Distributed MAS with simulated microgrid test system.

In grid connected mode, the generation agents minimise their $f_j(P_j(i))$ based on the real-time grid price signals at time i and send the respective power references. In island mode, the agents cooperate so the cheapest generation available is used first, constraint by the load agent messages.

The ESS agent optimises its cost function using explicit MPC, by the same constraints of the generator agents. Depending on the microgrid mode, the grid price or load agents are informed by the DF when a generator or ESS agent in the platform subscribes to it to send them ACL messages based on the time i read from the physical layer, allowing flexibility in the size of the microgrid and the capacity to adapt to changes in the schedule, as all schedules are updated continuously along the microgrid simulation.

IV. Test Case

The test microgrid and its scenarios are based on the optimisation problem from [10], which is composed of a micro turbine (MT), a fuel cell (FC), a battery, and a load connected to a single bus and to the main grid through a transformer. The components are modelled with the repository from [30]. The line and control parameters used are provided in Table I.

TABLE I
MICROGRID PARAMETERS

DGU Lines		**LCL filter**		**Inner loop gains**		**Outer loop gains**	
R	0.1 Ω	L grid	1.5 mH	P	1.5	I_P	1
X_L	0.002 Ω	C	2.6 mF	I	20	I_Q	15
V_L	400 V	L converter	10 mH				
f	50 Hz						

The microgrid was modelled in RT-LAB and using the OPAL-RT OP5700 real-time simulator as it's mentioned as a leader in Hardware-in-the-loop testing, in combination with JADE based MAS for power management [31]. The model

TABLE II

GRID PRICES FROM [10].

Hour	Euro ¢/kWh	Hour	Euro ¢/kWh	Hour	Euro ¢/kWh
1	2.5	9	15	17	6.2
2	2	10	40	18	4.4
3	1.5	11	40	19	3.7
4	1.3	12	40	20	5
5	1.2	13	15	21	11.9
6	2.1	14	40	22	5.3
7	2.3	15	21	23	3
8	3.9	16	19.7	24	2.7

TABLE III

DER PARAMETERS

DGU paramter	Micro turbine	Fuel Cell	ESS
P_{min} (kW)	6	6	-30
P_{max}(kW)	30	50	30
b (Euro ¢/kWh)	4.37	2.84	0
c (Euro ¢)	85.06	255.18	0

works in 3-phase at 400 Volts RMS from line to line at 50 Hz. The DGUs are modelled as a 1500 V DC source connected to a 2-level inverter with an LCL filter. The primary control method proposed is applied inside the RT-LAB model, while the secondary control composed by the JADE platform is in a external PC, interfaced as shown in Fig. 3.

Three cases for cost minimisation are presented, the low load, where the demand is lower than the distributed generation, the high load case, with load higher than DGU capacity, and a stand alone case where there is no exchange of power between the grid and the microgrid. In the grid connected scenarios it is assumed that it is possible to sell energy to the grid at the grid price. In Table II and III the parameters for the cost optimisation are provided.

V. SIMULATION AND RESULTS

The circuit model was tested with a simulation time step of 5e-5 seconds, for one day with every hour being represented by 4 seconds of simulation. The power management was also developed for offline optimisation in MATLAB applying heuristics to approach the global minimum cost for 3 solvers, genetic algorithm (GA), particle swarm optimisation (PSO) and pattern search (PS) as a point of comparison[1], along with the results from [10]. The problem is solved with an i7-6700 CPU at 3.40 GHz with 16 GB of RAM. The generation cost found plotted against computing time for 10 runs for each solver and each scenario is shown in Fig. 4. The time axis is presented in all cases in logarithmic scale.

The vertical left axis measures the cost found in euros, while the vertical right axis measures the relative difference to the benchmark total cost in [10] which used Multi-Stage Decision Programming (MSDP), calculated as the difference of the cost found and the MSDP cost divided by the MSDP cost, shown with a red line. GA refers to the fully heuristic approach and GA2 to the combination of the heuristic and numerical approach.

[1]Refer to the MathWorks Global Optimisation Tool box for more information about these solvers.

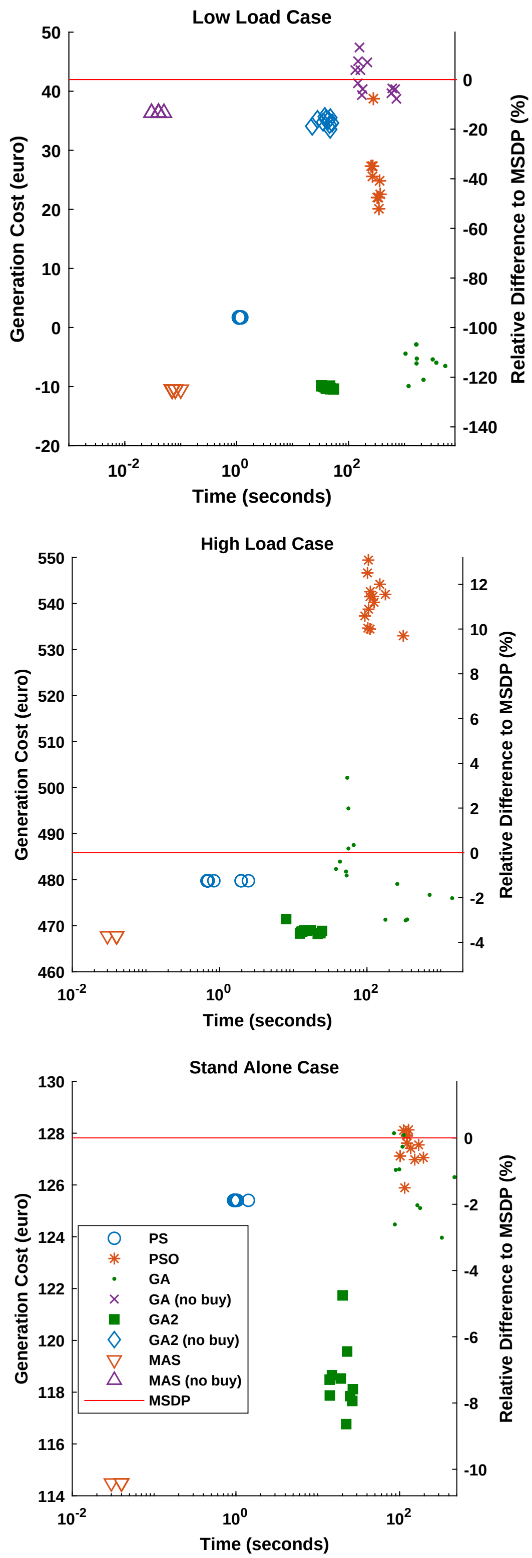

Fig. 4. Optimisation results. Top, low load case, middle, high load case, bottom, stand-alone case.

For the Low load case, an additional no buy policy is tested for GA, GA2 and MAS, as the DGUs capacity is higher than the load, no energy is supplied from the grid. For the High load and Stand-alone case, all solvers reach a relatively similar solution. A summary of the average costs

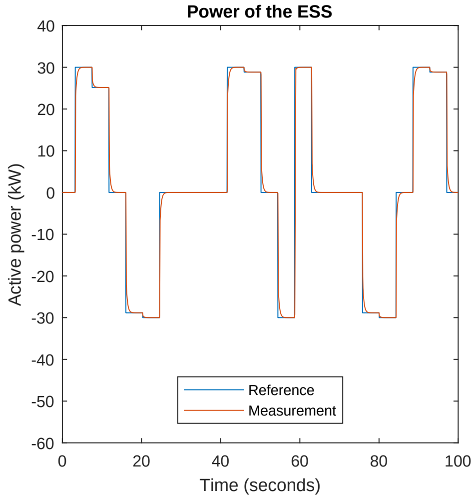

Fig. 5. Control response for the active power of the ESS

and calculation time for each solver is found in table IV, the stop criterion is a variation in the total cost from the previous iteration below 1e-6. In all cases it can be seen that the MAS approach is faster, taking milliseconds to obtain the power schedule, while the other methods take minutes and the result varies even with the same initial conditions. The MAS approach consistently reaches the global minimum in the 3 scenarios except in the no buy scenario of the low load case where the GA2 is able to find a slightly better solution, however the average calculation time required is 39.6 seconds compared to 40 milliseconds for the MAS approach.

TABLE IV
OPTIMISATION SUMMARY

Algorithm	Average cost (euro)	Average CPU time (seconds)	Method	Relative Difference to MSDP (%)
Low Load Case				
PS	1.71	1.11	Heuristic	-95.91
PSO	25.78	308	Heuristic	-38.57
GA	-5.81	2323	Heuristic	-113.84
GA (no buy)	42.06	325	Heuristic	0.21
GA2	-10.14	42.3	Combined	-124.16
GA2 (no buy)	34.82	39.6	Combined	-17.03
MAS	-10.49	0.08	Numerical	-124.99
MAS (no buy)	36.33	0.04	Numerical	-13.43
High Load Case				
PS	479.78	1.03	Heuristic	-1.25
PSO	540.47	132.6	Heuristic	11.23
GA	481.9	263	Heuristic	-0.82
GA2	468.97	16.2	Combined	-3.47
MAS	467.82	0.39	Numerical	-3.71
Stand Alone Case				
PS	125.4	1.01	Heuristic	-1.88
PSO	127.42	134.7	Heuristic	-0.30
GA	129.16	172	Heuristic	1.05
GA2	118.52	20.5	Combined	-7.27
MAS	114.49	0.39	Numerical	-10.42

In Fig. 5 the response of the DGU to the set points sent by the ESS agent are presented. Smooth operation can be seen for reference changes from -30kW to 30kW. Figure 6 illustrates compliance with the GB National Electricity Transmission System Grid Code.

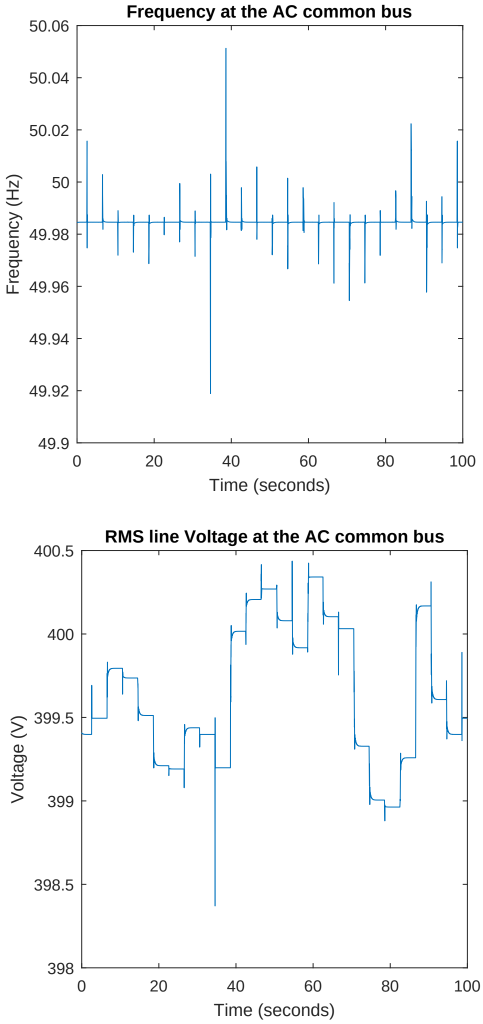

Fig. 6. The frequency and voltage variation are within the 50 Hz $\pm 1\%$ range and the 400V $\pm 5\%$ range.

VI. CONCLUSION

This paper presents a primary controller with stable system's voltage and frequency while the power flows from and to the microgrid, and a secondary controller of MAS to minimise costs of energy generation as a global objective while each agent minimises its own cost function. The global optimisation is done with time-based cooperating agents. The results show generation cost improvements while the constraints are met when compared to the other solvers.

The energy management capacity of the MAS control can produce consistent, fast and optimal results compared to the heuristic methods, the small calculation time allows real-time optimisation as the power schedule is generated while the simulation is running.

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