Studies on Control Architectures and Optimization of Islanded AC and Hybrid AC/DC Microgrids

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This thesis is dedicated to extensive studies on the control and optimization of islanded AC and hybrid AC/DC microgrids. It presents model formulations and control algorithms for microgrids integrated with different types of distributed generators, power converters, renewable energy sources, battery systems, and power devices.

A conceptual three-level hierarchical control scheme can be defined to classify the objectives, operation capabilities, and time-response in an energy management system of a microgrid. The control and optimization approaches presented in this work are classified as secondary-level controllers, addressing some of the most common objectives for this level, such as power loss minimization, AC frequency and DC voltage restoration, proportional active power dispatch, battery systems coordination, and optimal reconfiguration. Also, different system architectures were explored and studied in this research project, including a fully distributed optimization approach, a consensus-based distributed control system, and a centralized learning classifier system. Since the islanded microgrids lack a slack bus, special emphasis is made on always maintaining the internal supply-demand power balance. System stability is considered in all cases by maintaining bus voltages and AC frequency at operational levels. It is worth mentioning that, since the microgrids in these scenarios are completely islanded, tertiary-level controllers cannot be implemented.

The distributed generators modeled in this dissertation are classified as dispatchable and non-dispatchable. Dispatchable generation units are those whose output power can be controlled according to set-points established either by the energy management system operator (directly or remotely) or obtained through external signals typically acquired at the coupling point (i.e., diesel generators, fuel cells). In islanded microgrids, they usually have droop-based functions embedded at their primary level controller, which allow them to dynamically change their output power proportionally to the control signals they receive or sense at the coupling point. Contrarily, non-dispatchable generation units are those in which output power cannot be directly controlled, regularly depending on external factors and weather conditions (i.e., photo-voltaic systems, wind turbines). They typically have primary controllers that maximize their output power, such as the maximum power point tracking technique.

On the other hand, the power devices modeled in this work, such as battery systems and interlinking converters, possess some dispatchable characteristics and their bi-directional converters can be controlled by droop functions at their primary level. However, they are always subject to other status variables, such as the state of charge of the batteries and the availability of power to convert.

The major original contributions reported in this thesis include:

- The development of power level (i.e., steady state) mathematical models of islanded AC and hybrid AC/DC microgrids that include different types of energy sources, power converters, battery systems, and power devices;

- The design of a fully distributed power loss minimization approach for AC droop-based islanded microgrids that are composed of photo-voltaic and battery systems;
• The development of a consensus-based distributed control of hybrid AC/DC islanded microgrid that addresses different secondary control objectives, such as proportional active power dispatch, AC frequency, and DC voltage restoration, inter-linking converter control improvement and battery systems coordination;

• The construction of a random forest classifier system for AC reconfigurable islanded microgrids that minimizes the power loss by changing the physical topology of the system to the optimal configuration according to the generation and loading levels.

Simulations of the proposed control and optimization approaches are presented, validating their respective performance with different system topologies and dynamic power generation and loading levels.
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This thesis contains work that has been published and/or prepared for publication during my PhD study since 2017, which are rearranged and slightly modified to achieve consistency and coherence in the content.

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List of Abbreviations

AEMO  Australian Energy Market Operator
BCO   Bee Colony Optimization
BESS  Battery Energy Storage System
DE    Differential Evolution
DER   Distributed Energy Resource
dg    Distributed Generator
EMS   Energy Management System
ES    Electric Spring
GA    Genetic Algorithm
GSO   Group Search Optimization
ILC   Interlinking Converter
MAS   Multi-Agent System
MPPT  Maximum Power Point Tracking
NWP   Numerical Weather Prediction
P&O   Perturbation and Observation
PCC   Point of Common Coupling
PSO   Particle Swarm Optimization
PV    Photo-voltaic
RCS   Remote Control Switch
RES   renewable energy source
SoC   State of Charge
UPS   Un-interruptible Power Supply
VSI   Voltage Source Inverters
Chapter 1

Introduction

1.1 Research Objective

The initial objective of this research thesis is to deeply study, analyze, and categorize the control and optimization strategies of islanded AC and hybrid AC/DC microgrids. Therefore, an extensive literature review of fundamental knowledge and theories underpinning the composition of microgrids is initially presented. The second objective is to address the optimization challenges that arise with the ever-increasing penetration of renewable energy sources and battery energy storage systems. Understanding that the composition of microgrids is continuously becoming more diversely integrated and complex, the research question that this thesis is dedicated to answer is: what control and optimization approaches are suitable for what specific type of microgrid configuration? To address this question, centralized, decentralized and distributed control architectures are proposed, to achieve secondary level objectives, such as power loss minimization, proportional active power dispatch, and battery energy storage systems coordination, among others. In each of the following chapters, details on the novelty of the proposed approaches is highlighted. Interim conclusions are drawn in every chapter, detailing advantages, drawbacks, and limitations of the proposed strategies. An overview of the classification of microgrids is given in the following section.

1.2 The Concept of Microgrid

With the ever-increasing demand of electricity, traditional power systems with centralized generation and long transmission lines are facing unprecedented challenges in their capacity and reliability. Updating the existing network may be not feasible or economically not viable, especially for remote growing communities with the costs of construction and maintenance of the transmission lines considerably high. The idea of a more flexible electric grid with DERs geographically close to the power demand led to the conceptualization of microgrids. In this dissertation, we define a microgrid as a geographically close cluster of power sources, loads, and power devices that can function either in grid-connected or islanded mode. These power sources can be fuel-based generators or RESs, usually coupled with electronic converters and inverters. BESSs coupled with bi-directional converters can also be included in a microgrid in order to cope with surplus and shortage in electric power generation. In the first instance, the top priority of a microgrid is to maintain voltage and frequency stability of electric
power supplied to the loads, using the available resources and data; however, taking advantage of the
flexibility of DERs and BESSs, the optimal power flow problem in terms of power losses and generation
costs can be addressed. The performances and the optimization objectives of a grid-connected and an
islanded microgrid may be similar; in fact, an islanding procedure for a grid-connected microgrid in
case of dangerous disturbances or faults in the main grid is a self-preserving strategy that has been
widely studied. However, for a geographically remote microgrid that is far from the main grid but close
to other microgrids, coupling with one or multiple microgrids can be implemented as a healing strategy
to maintain and reinforce the voltage and frequency stability. Microgrid controllers, with centralized,
decentralized, and distributed topologies, must drive the system through the normal operation and
contingency stages to ensure stability and optimality.

A microgrid is a well geographically defined cluster of power sources, loads and energy storage
devices that have the flexibility of working connected to the main grid or islanded [2]. Traditionally,
DGs in microgrids are fossil-fuel fired generators, which consume underground mineral sources such as
coals, diesel, etc. However, due to the concern of unsustainability of these power plants, especially
the negative effects of burning fossil fuels on the environment, renewable energy sources have gain
great popularity in recent decades, which are clean and inexhaustible. This leads to the necessity of
designing new strategies for exert the highest efficiency through the coordination of a diverse range of
power sources. The control of microgrids faces more complex and concerning challenges than those of
the traditional power grid, in terms of system stability, load balancing, and power flow optimization.
The high penetration of RESs, which rely heavily on weather conditions, naturally compromises the
supply/demand balance. Therefore, BESSs have been introduced to cope with the surplus and shortage
of power generation. Additionally, diverse strategies and control approaches have been developed to
alleviate the power generation uncertainty, such as the use of controllable loads and load shedding
strategies, the integration of weather and load forecast information to predict future generation and
loading conditions, the coupling and decoupling of microgrids to a main grid or other microgrids,
among others.

The integration and control of microgrids brings new challenges and optimization problems to
address, in order to get full advantage of the benefits of the distributed generation flexibility. Therefore,
as research in the subject advance, more complex control strategies are designed to tackle these
challenges and achieve optimal performance of microgrids when integrating different types of DERs,
power devices, and forecast data [3]. Some of the new challenges include, but are not limited to [3]:

- Adequate dispatch of power generation units for proper load sharing, according to their capacities
  and costs.

- Proper management of BESS for healthy charge and discharge stages, including their SoC in
  their dispatch functions.

- Design of optimization strategies to minimize power loss, power generation costs, and carbon
  emissions.
1.2. THE CONCEPT OF MICROGRID

- Integration of voltage and frequency stability control techniques for coping with the possible lack of inertia in generation units, due to the increased penetration of power-electronics-interfaced distributed generators.

- Development of control and cooperative techniques that allow plug-and-play or semi-plug-and-play introduction of DERs to the microgrid.

- Design of protection strategies in order to ensure voltage and system frequency stability for critical loads.

- Design of self-healing strategies for microgrids in case of power generation deficiency and/or instability, such as coupling and decoupling to/from a main grid or other microgrids.

- Reach full integration of AC and DC generation units, loads and power devices, seamlessly.

In order to overcome these performance, optimization and protection challenges, researchers have conceptualized the implementation of energy management systems with different objectives, configurations, and control capabilities. Since microgrids can have different characteristics depending on the topology, objectives, information available, types of DERs, BESSs, loads, etc, many different strategies have been proposed:

- Regarding the DERs and the proper load sharing, droop-based techniques (active power vs system frequency and reactive power vs voltage) have been widely used in AC microgrids. In DC microgrids, the droop-based functions typically involve bus voltage vs output current.

- In terms of optimization, the most common strategies intend to minimize power loss, generation costs, or carbon emissions, using heuristic optimization algorithms [4], such as GA, PSO, DE, among others.

- For BESSs management and coordination, droop-based techniques that consider system frequency (in AC microgrids) and bus voltages (in DC microgrids), and batteries SoC are the most common approaches.

- If controllable loads are included in a microgrid, strategies for shedding non-critical loads in cases of power generation deficiency have been proposed.

- When RESs are included and weather forecasting information is available, predictive and scheduling strategies are commonly implemented to predict and guarantee power availability in a planning horizon.

- When load forecasting information is available, predictive and scheduling strategies are also implemented for the same previously mentioned reason.

- If a microgrid is designed to function as an autonomous islanded system, techniques that enable its coupling with the main grid and/or other microgrids are used as a self-healing strategy for power insufficiency.

- If a microgrid usually works in grid-connected mode, decoupling procedures are devised to disconnect the microgrid from the main grid in case of instability in the main grid.
1.3 Microgrid Operation Modes

Regarding the physical topology and operation mode, a microgrid can work in either islanded mode or grid-connected mode. Depending on the hardware and control capabilities of the system, it may be able to transition between these two modes in order to ensure voltage and frequency stability for end-users. However, remote microgrids that are geographically located away from a main grid are designed to work in islanded mode full time; while other microgrids are designed to operate all the time in grid-connected mode. The intended operation mode of a microgrid determines the control techniques of the DGs, BESSs, and other power devices. Also, the optimization objectives can be slightly different in both modes.

1.3.1 Islanded Mode

An islanded AC or DC microgrid does not have an interconnection with a main grid, which means that all the loads must be supplied by the generation units from inside the microgrid. The supply-demand power balance must be met and guaranteed by the DERs (dispatchable and non-dispatchable), BESSs, and other power devices. This implies that any change or fluctuation in the loads must be balanced solely by the dispatchable DERs and BESSs, since RES units are non-dispatchable and their output power may be intermittent and somehow unpredictable. However, BESSs and their bidirectional inverters are constrained by their power capacities and energy density, and their contribution to the power balance may be limited as well. Hence, in order to improve the resilience of islanded microgrids and deal with power imbalances, other security strategies are implemented, such as load shedding when the power demand is greater than the power generation, and power curtailment when the power generation is greater than the power demand; nonetheless, these are undesired stages for a microgrid. Therefore, proper sizing of islanded microgrids is known as an important problem to address for researchers and electricity utilities, for the purpose of getting the best benefit-cost ratio.

1.3.2 Grid Connected Mode

A grid-connected microgrid is connected to a main grid through the PCC. The supply-demand balance is not as critical as in an islanded microgrid, since any major power imbalance beyond the capabilities of dispatchable DERs and BESSs can be compensated by importing or exporting power from the main grid. Voltage and frequency stability are generally granted by the main grid, known as the slack bus in power flow analysis. This relaxation on power balance and stability requirements grants the connected-microgrids with the flexibility to address and explore other optimization problems, such as the cost optimization of imported/exported power.

1.4 Classification of Control Architectures

In general, a conceptual three-level hierarchical control structure can be defined to classify the objectives, operation capabilities, and time-response, in a control system of a microgrid [1, 3, 5–8]. The primary level is the basic control loop of DGs, BESSs, and other power devices in a system. The secondary
1.4. CLASSIFICATION OF CONTROL ARCHITECTURES

Figure 1.1: Hierarchical control structure [1].

level is, at first instance, in charge of the restoration and stability of a system; however, optimization objectives can be addressed as well at this level. The tertiary level is in charge of establishing a connection and optimizing the power flow between a microgrid and a main grid or other microgrids. Figure 1.1 shows a simplified diagram of the hierarchical structure. Figure 1.2 depicts the control levels in a simple microgrid example.

Figure 1.2: Hierarchical control in a microgrid: primary, secondary and tertiary levels [1].
CHAPTER 1. INTRODUCTION

1.5 Primary Control

This is the basic control loop of DERs in microgrids, and has the fastest time response (in the order of milliseconds) among all three control levels. Only local measurements of bus voltage, current, and system frequency are used to construct the inner control signals needed to maintain the output power and bus voltage at the required set-points, in AC and DC microgrids. In synchronous generators, voltage and output power are controlled by the governor, the voltage regulator and the inertia of the machine, typically using droop-based control schemes (active power-system frequency and reactive power-bus voltage), in AC microgrids [9]. The non-dispatchable DGs, such as solar photo-voltaic (PV) systems and wind turbines, are typically designed to work under MPPT techniques, to maximize their power generation. In VSIs, such as UPSs, the power sharing can also be emulated by using droop characteristics [10]. In DC microgrids, dispatchable units typically use droop-based controllers that involve bus voltage and output current to create the inner loops control signals [11–16].

The main advantage of this control strategy is that it does not require a communication system to achieve the active power load sharing, since the microgrid frequency (in AC microgrids) and bus voltages (in DC microgrids) can provide sufficient information for computing the active power dispatch of each DG as a function of its capacity. However, the main disadvantage in AC microgrids is that reactive power is not proportionally shared among the DGs, since it is highly related to the voltage magnitude. In DC microgrids, line resistors may cause bus voltage deviations, subsequently causing disproportional active power dispatch. Nevertheless, there are some proposed solutions implemented in the secondary level control for coping with this drawback [9,17]. Another problem in AC microgrids is that active and reactive power can only be properly decoupled when the equivalent impedances connecting the DERs are mainly inductive; however this problem is also addressed in [18–20], where solutions for resistive and complex impedances are proposed. In this dissertation, AC microgrids are considered to be inductive in order to generalize and simplify their primary level coupling, while focusing in the secondary level control and optimization objectives.

Multiple variations to the droop-based control strategies have been proposed, to achieve different objectives in various scenarios [10,21–24]. Also, droop relations based on generation costs have been proposed in order to optimize, at a certain degree, the power generation without compromising the system stability [25,26]. Non-linear relations have also been used in order to achieve an even higher degree of optimization [27–29]. Dynamic droop relations have been explored in [17].

1.5.1 Droop Control in AC Microgrids

Linear droop control is the most common primary level control strategy of dispatchable DGs, which is widely implemented due to its simplicity and robustness. As mentioned before, in AC microgrids, it employs system frequency and bus voltage deviations caused by the load variations to construct the control signals, in order to adjust the output power. In AC microgrids, the classical relations between real power and frequency, and reactive power and voltage can be expressed as [9,30]:

\[ \omega = \omega_{\text{max}} - m_{\text{DG}} \cdot P_{\text{DG}}, \]  

(1.1)
1.5. PRIMARY CONTROL

\[ |V_{AC}| = V_{AC,max} - n_{DG} \cdot Q_{DG}, \]  
(1.2)

where \( \omega_{\text{max}} \) and \( V_{AC,max} \) are the system frequency and bus voltage maximum values, \( P_{DG} \) and \( Q_{DG} \) are the active and reactive powers injected by the DG, and \( m_{DG} \) and \( n_{DG} \) are the droop coefficients, computed from:

\[ m_{DG} = \frac{\omega_{\text{max}} - \omega_{\text{min}}}{P_{DG}^{\text{cap}}}, \]  
(1.3)

\[ n_{DG} = \frac{V_{AC,max} - V_{AC,min}}{Q_{DG}^{\text{cap}}}, \]  
(1.4)

where \( \omega_{\text{min}} \) and \( V_{AC,min} \) are the system frequency and bus voltage minimum values, and \( P_{DG}^{\text{cap}} \) and \( Q_{DG}^{\text{cap}} \) are the active and reactive power capacities of the DG. Figure 1.3 shows the \( P - \omega \) linear relations of two DGs in an AC microgrid.

![Figure 1.3: Typical active power vs frequency droop functions of two DGs in AC microgrids.](image)

1.5.2 Droop Control in DC Microgrids

\[ V_{DC,max} \]

\[ V_{DC,min} \]

\[ P_{DG1}^{\text{cap}}, P_{DG2}^{\text{cap}}, P_{MG}^{\text{cap}} \]

\[ P_{DG1}^{\text{cap}}, P_{DG2}^{\text{cap}}, P_{MG}^{\text{cap}} \]

![Figure 1.4: Typical active power vs bus voltage droop functions of two DGs in DC microgrids.](image)

Similar to its AC counterpart, the DC droop control is widely used in power controllers for dispatchable DGs in DC microgrids. The elemental idea is to dynamically adjust the generated power as a function of the power demand and bus voltage droop. The DC bus voltage reference of the DG increases and/or decreases when there is a change in the current demand, according to the droop
function formulated as follows:

\[ V_{DC} = V_{DC,max} - u \cdot P_{DG}, \]  

(1.5)

where \( V_{DC,max} \) is the nominal bus voltage, and \( u_{DG} \) is the droop coefficient, obtained from:

\[ u_{DG} = \frac{V_{DC,max} - V_{DC,min}}{P_{cap}_{DG}}. \]  

(1.6)

where \( V_{DC,max} \) and \( V_{DC,min} \) are the bus voltage deviation limits and \( P_{cap}_{DG} \) is the power generation capacity of the DG. Figure 1.4 shows the linear relations of two DGs in an DC microgrid.

### 1.5.3 Droop Control of Interlinking Converters in Hybrid AC/DC Microgrids

![Droop function that governs the active power conversion in an ILC.](image)

Hybrid AC/DC microgrids are composed of both AC and DC loads, energy sources, and power devices. Nowadays, the hybrid power system is considered as one of the most promising future power system configurations, accommodating a high penetration of distributed renewable energy sources [31]. In hybrid AC/DC microgrids, the ILC controls the power flow between the AC and DC sub-grids. Droop functions governing the amount of power being converted are widely used [23, 32], as a fully distributed way of coping with loading fluctuations. Using only normalized local measurements of AC frequency and DC bus voltage, the ILC can estimate the loading levels of both sub-grids, and determine the direction and amount of active power to convert. The normalization equations are defined as follows,

\[ \hat{\omega} = \frac{\omega - (\omega_{max} + \omega_{min})/2}{(\omega_{max} - \omega_{min})/2}, \]  

(1.7)

\[ V_{DC} = \frac{V_{DC} - (V_{DC,max} + V_{DC,min})/2}{(V_{DC,max} - V_{DC,min})/2}, \]  

(1.8)

where \( \omega_{max} \) and \( \omega_{min} \) are the frequency deviation limits, and \( V_{DC,max} \) and \( V_{DC,min} \) are the DC bus voltage deviation limits. Subsequently, the difference between \( \hat{\omega} \) and \( \hat{V}_{DC} \), \( \Delta e \), is used to determine the active power converted by the ILC, as follows,

\[ \Delta e = \hat{\omega} - \hat{V}_{DC}, \]  

(1.9)
where $\kappa_{ILC}$ is the droop coefficient, a constant defined from the active power converter capacity, as follows,

$$\kappa_{ILC} = \frac{\Delta e_{\text{max}}}{2P_{\text{cap}}^{\text{ILC}}}.$$  

(1.11)

Figure 1.5 depicts graphically the droop function governing the active power flow at the ILC.

1.5.4 Droop Control in Battery Energy Storage Systems

The typical droop strategy cannot be directly implemented in BESSs, since it only considers the power capacity of the inverters, which would cause over-charge or over-discharge of batteries with the ignorance of battery SoC, in both AC and DC microgrids. Therefore, to balance the power contribution of each BESS in a microgrid, the power injection must be based not only on its capacity, but also on its SoC [33]. Thus, droop-based primary controllers that consider the SoC of BESS have been extensively explored in [34–44]. Figure 1.6 shows graphically a modified droop-based primary controller where the active power injected/absorbed by the BESSs is a function of the frequency and its SoC, in AC microgrids. Also, fuzzy logic-based strategies have been developed in order to balance the SoC of the BESS and to manage the charge and discharge stages of energy storage systems [45–47].

1.6 Secondary Control

This control level is typically called EMS, and is in charge of the stability and optimality of the microgrids. In islanded AC and DC microgrids, this is the highest level of hierarchical control, since there are no grid-coupling options that require a tertiary level controller. Secondary controllers can determine the control set-points of the primary controllers of DGs and BESSs, in order to fulfill stability and optimality objectives. This control level works in a larger time scale (in the order of tens of seconds
or minutes) than the primary level, and usually relies on a basic low-bandwidth communication system for data transmission. The dispatch level and control set-points of the primary controllers is usually computed at every time-step, making the design of this control level a real-time optimization problem.

Also, when weather and load forecast information is available, this control level can build dispatch schedules for DERs, BESSs, and controllable loads in a planning horizon of minutes, hours, and days, in order to achieve the system objectives and guarantee the power supply in the system [48–50]. Figure 1.7 shows what kind of information can be gathered by a centralized EMS and the control signals generated to be transmitted to the control units [48].

Typically, this is a centralized controller that gathers all kind of information available from the microgrid, processes it and takes actions; however, distributed control strategies based on MASs have been recently proposed. Under the distributed control structure, every unit can be represented as an agent, with a certain degree of intelligence and autonomy. The agents work together in a cooperative manner in order to fulfill the local and global control objectives [51]. However, the controllers design becomes more complex and difficult to implement in real-world applications, due to the need of higher computational power to achieve the control system objectives.

1.6.1 Optimal Power Flow

The control objectives of secondary level controllers involve stability and optimality of the microgrid. Regarding the latter, energy management systems use all information available to construct and solve the optimal power flow in AC and DC microgrids. Similar to the optimal power flow problem in tradi-
tional power systems, the optimization objectives in microgrids may refer to one or some of the following:

- Minimize power loss in transmission lines,
- Minimize power generation cost,
- Minimize carbon emissions or fuel consumption of the system,
- Minimize load shedding operations,
- Minimize imported power from the main grid through the PCC (in grid connected microgrids),
- Minimize cost of imported power from the main grid through the PCC (in grid connected microgrids) \[52\].

These optimization problems are non-linear and some times multi-objective, therefore, heuristic algorithms are widely used to solve them, such as GA, PSO, DE, GSO, and BCO, among others. When information of future weather conditions, load demand, and electricity prices is available, the optimization problem becomes a multi-objective scheduling problem for a particular planning horizon. These optimization problems must be addressed to ensure and reinforce the optimal performance of the microgrid and taking maximum advantage of the renewable resources.

In this dissertation, the power loss minimization objective is extensively explored, as the lack of slack bus in islanded microgrids poses a more pressing need of maintaining the power supply/demand power balance, to which reducing the power loss contributes \[53–55\].

### 1.6.2 Weather and Load Forecast

One of the main advantages of microgrids is the flexibility to facilitate the inclusion of RESs. However, the power generated by these units heavily relies on weather conditions, and may be intermittent and/or unpredictable. At all times, EMSs must be able to maintain system stability in terms of supply/demand power balance, voltage levels, and system frequency (in AC microgrids), even in cases of sudden changes of loading levels or atmospheric conditions. Therefore, future weather and load information can be critical to build pre-dispatch schedules for the DERs and charging/discharging schedules for the BESSs. There are multiple approaches for constructing weather and load forecast models, such as the NWP. The use of different planning horizons can be found in literature, spanning over minutes, hours, and days \[52, 56, 57\]. In this regard, machine learning approaches, such as neural networks, have been extensively used to construct these forecasting models, exploiting their prediction capabilities \[58–63\].

### 1.6.3 Microgrid Reconfiguration

Reconfigurable microgrids allow controlled changes in the grid topology to redirect and redistribute the power flow, using control switches distributed along the system. Particularly in the case of islanded
CHAPTER 1. INTRODUCTION

microgrids, the disconnection from the main grid compromises both the power balance and stability of the system. Also, the non-dispatchable nature of the RESs limits the control variables needed to formulate an optimization problem, as they typically work under an MPPT control technique. Therefore, taking into account the limitations of the power dispatch of DGs in these scenarios, a central secondary controller can identity which grid configuration is optimal (in terms of stability and/or power loss) for a particular power profile of demand and power generation, in a particular time of the day [64–66]. The control switches grant the EMS with binary (closed/open) control variables that can be used to formulate an optimization problem, even in scenarios where the system is mainly composed by non-dispatchable RESs. Figure 1.8 shows an example of a 42-Bus islanded microgrid with seven reconfiguration control switches.

Figure 1.8: Reconfigurable 42-Bus system.

1.6.4 Load Shedding

Load shedding strategies can be used by the EMSs in cases where power generation is irremediably lower than power demand in islanded AC and DC microgrids [56]. Generally speaking, loads are classified as critical loads and non-critical loads. The priority of the EMSs must be to provide stable and uninterrupted power supply for the critical loads, and in case of power shortage, non-critical loads can be gradually disconnected (known as load shedding). If a pre-dispatch schedule can be computed using weather and load forecasting data, the EMSs can identify in advance whether a load shedding stage is needed and, if so, perform it systematically and safely. Therefore, one of the optimization objectives for the EMSs is to minimize the load to be shed [56,67–71]. The use of ESs is also proposed as an alternative for controlling the power dissipation of some non-critical loads that can work within a range of power levels [72–74].
1.6. SECONDARY CONTROL

As mentioned before, the EMSs control architectures of AC and DC microgrids can be classified as centralized or decentralized [3]. In a fully decentralized architecture, all units (DERs, BESSs, power devices) have total autonomy of their actions, relying only on local measurements of bus voltage, current, and frequency, at its point of connection. There is no communication between units, therefore they are never fully aware of the overall status of the entire system, heavily limiting their capacity to address complex optimization objectives [75].

On the other hand, in a centralized control architecture, a central controller continually gathers data from the system and determines the actions and power set-points of all units at every time-step. Therefore, the performance of the system relies on an extensive communication system and the computational capacities of the central controller [48,49]. Naturally, more complex system optimization objectives can be addressed under this architecture, since the central controller is usually capable of performing power flow analysis and running computationally expensive optimization algorithms.

In real-world applications, fully decentralized architectures without communication or coordinated actions are difficult to design, due to the strong direct and indirect relations among the units that objectively exist. On the other hand, the main drawback of centralized architectures, is the strong dependence on a communication system that can be expensive and insecure.

Apart from centralized and fully decentralized architectures, and as mentioned before, a third class

Figure 1.9: Structure of a microgrid with critical and sheddable loads.
of control architectures can be labeled as distributed, in which the system is controlled by autonomous agents connected by a sparse communication system [76–79], as seen in Figure 1.10. Units have their local control objectives of power dispatch and voltage regulation, but also contribute to achieve global system optimization objectives.

1.7 Tertiary Control

This is the highest level of control in AC and DC microgrid systems. It works on a larger time scale (minutes or hours) than the secondary control and coordinates the connection and disconnection of the microgrids with the main grid or other adjacent microgrids [80]. If two or more microgrids are coupled, this control level is to optimize the power flowing through the PCC [80]. If the microgrids are completely islanded and never to be coupled, this control level is not implemented. Figure 1.11 shows how the tertiary control is in charge of selecting the best candidate to be coupled among a group of microgrids.

Coupling microgrids as a strategy for self-healing has been proposed recently for islanded microgrids. The main idea is to import or export power from or to the interconnected microgrids when the mismatch between the generation and the demand cannot be managed with the existing resources within a microgrid. In this case, the unstable microgrid can require assistance of a stable microgrid. The coupling cannot undermine the stability of any of the participating microgrids; this is addressed by performing a stability analysis prior to coupling. The coupling procedure is performed through the tertiary control, which is also in charge of the optimization of the power flowing through the PCC [81–85]. The process of decoupling of a microgrid has also been studied, where the main objective is to minimize the power flow imported/exported at the PCC, for the purpose of creating a safe disconnection and minimizing system disturbances [30,75].
1.8 Thesis Outline and Publications

This thesis is supported by publications completed during my PhD study, and it is outlined as follows. Chapter 1 presents background information and critical literature reviews on the subject of the research project and also provides information on thesis outline and publications. In Chapter 2, a power flow algorithm for islanded AC microgrids that can seamlessly include droop-based dispatchable distributed generators, non-dispatchable renewable energy power sources, and battery energy storage systems, is formulated, as a simple tool to observe the different stages an islanded microgrid go through during normal operation. Simulations results validate the accuracy of the model. In Chapter 3, a fully decentralized adaptive droop optimization strategy for inverters is proposed for minimizing power loss during power transmission in islanded AC microgrids integrated with solar photo-voltaic systems. From a hierarchical point of view, the proposed control architecture of the DGs encompasses both the primary and secondary levels, in a decentralized plug-and-play manner. The secondary level control has the objective of minimizing the power loss in the system, which is achieved by the proposed adaptive droop functions. In Chapter 4, a distributed control architecture for hybrid AC/DC islanded droop-based microgrids is proposed to address the most common cooperative objectives, including AC frequency...
and DC voltage restoration, BESSs charge/discharge coordination, proportional active power dispatch
and interlinking converter power flow control. In Chapter 5, a random forest classifier is developed
as an approach to find the optimal configuration of islanded AC microgrids with high penetration
of renewable sources. The proposed classifier is a predictive approach of machine learning theory,
implemented as a centralized controller, and relying on an off-line training stage. Finally, a conclusion
is drawn in Chapter 6 where a brief discussion is presented and possible future work is listed. This
thesis is comprised of a number of papers that have been published or prepared for publication during
my PhD study. Below is the list of publications produced through the course of my PhD project.
Chapter 2

Power Level Model of AC Isolated Microgrids

ABSTRACT

There are widely known techniques for solving the power flow of AC power systems at a power level (to find steady-state variables, such as active and reactive powers, bus voltages, and line currents), but none of them can be directly applied to AC islanded microgrids. The main reason is that, in a large-scale power grid, the slack bus behaves as an infinite power source that can compensate to any load fluctuation, and maintains coupling point bus voltage and system frequency. But in islanded microgrids, none of the distributed generators can be considered as a slack bus, due to their relatively small power generation capacities. Therefore, all bus voltages and system frequency are also variables to be found in the power flow formulation. Furthermore, the dispatchable distributed generators typically have droop-based primary level controllers, in order to collaborate with the supply-demand power balance, proportionally to their power capacities. This directly implies that their active and reactive power generation depends on the total power demand of the system, adding more variables to be found to the problem. In this chapter, a power flow algorithm for islanded AC microgrids that can seamlessly include droop-based dispatchable distributed generators, non-dispatchable renewable energy power sources, and battery energy storage systems, is formulated. Simulation results verify the performance. Posteriorly, a conclusion is drawn, followed by a brief discussion on current trends and future work in the subject.

The content of this chapter is mainly based on and modified from the following publication:

2.1 Introduction

An islanded AC microgrid lacks an interconnection with a main grid, which strongly compromises the supply-demand power balance. It implies that all the loads must be supplied by the generation units within the system. Thus, to guarantee the power balance at all times, all DERs (dispatchable and non-dispatchable) and BESSs available in the system have to contribute to accommodate any change or fluctuation in the loading levels. Therefore, linear droop controllers are the most common primary level control strategies of dispatchable DGs in islanded microgrids. Their simplicity and robustness allow the units to contribute to the total power demand, proportionally to their power capacities.

2.2 System Model

The system model integrates loads, distributed generators, transmission lines, and BESSs. Each of these models react significantly to variations on the system frequency and bus voltages, reason why these have to be included on their respective formulations. Also, due to the lack of an infinite capacity slack bus, and based on the concept of islanded microgrid where all DGs have relatively small capacity, all dispatchable units with droop-based primary controllers have to contribute to the total power demand, proportionally to their power ratings.

2.2.1 Generation model

In this chapter, the active generation units are also called RES-BESSs units, due to their internal composition, as presented in [34] and [46]. These units are integrated by photo-voltaic systems and BESSs. Photo-voltaic systems have non-dispatchable characteristics that depend on weather conditions, while the BESSs have charging/discharging capabilities that depend on system and inner variables. Therefore, the resulting units have limited dispatchable characteristics granted by the BESSs. Figure 2.2 depicts the construction of a RES-BESS unit. At a power level, these units are modeled as grid-forming DC-AC converters that contribute to the frequency and bus voltage stability [37,86]. It is assumed that the photo-voltaic systems have primary controllers that maximize their output power, such as the MPPT technique. Thus, the internal power balance of a RESS-BESS unit can be formulated as follows:

\[ P_{RB} = P_{PV} + P_{BESS}, \]  

where \( P_{RB} \) is the active power injected by the RES-BESS unit to the microgrid, \( P_{PV} \) is the active power generated by the photo-voltaic system, and \( P_{BESS} \) is the power injected or absorbed by the battery system. Consequently, using an adaptive droop control approach, the decoupled active and reactive power equations of the DC-AC inverter, coupled to the system through an inductive impedance, can be expressed as follows:

\[ P_{RB} = P_{PV} + \frac{1}{m_{RB}} \cdot (\omega_{max} - \omega), \]  

\[ Q_{RB} = \frac{1}{n_{RB}} \cdot (V_{max} - V), \]
2.2. SYSTEM MODEL

where $\omega_{\text{max}}$ and $V_{\text{max}}$ are the maximum frequency and bus voltage and $m_{RB}$ and $n_{RB}$ are the adaptive droop coefficients, computed as a function of the SoC of their batteries as follows:

$$m_{RB} = \begin{cases} 
1 & \text{for } \omega \geq \omega_n, \\
1 - \frac{1}{\text{SoC}_{RB}} & \text{for } \omega < \omega_n,
\end{cases}$$

$$n_{RB} = \frac{V_{\text{max}} - V_{\text{min}}}{Q_{RB}^\text{cap}},$$

where $\text{SoC}_{RB}$ is the SoC of the BESS, $P_{\text{cap BESS}}$ is the injecting/absorbing instant power capacity, and $Q_{RB}^\text{cap}$ is the reactive power capacity of the unit. So that, when the system frequency is above the nominal, the BESS within the unit absorbs active power from the photo-voltaic system (if available). Contrarily, when the system frequency is below the nominal, the BESS injects power to the microgrid, along with the photo-voltaic system. As a result, the BESS can only be charged by the photo-voltaic system, and not by other generation units in the system. Also, the inclusion of the SoC in the droop function guarantees that, in case the system is overloaded, the unit with higher stored energy injects more power into the microgrid. On the other hand, if the system is underloaded, the unit with lower stored energy absorbs more power from its photo-voltaic system to charge its BESS. This way, all BESS in the system tend to maintain the same SoC over time, even with different energy storage capacities. Figure 2.1 shows graphically the droop function controlling active power injected by the RES-BESS units as a function of the SoC of the batteries and the system frequency.

![Figure 2.1: Active power dispatch of the RES-BESS unit.](image)

2.2.2 Network model

As stated before, system frequency is a variable in islanded microgrids. Therefore, similarly to the characteristics of loads, the admittance matrix $Y_{bus}$ is a function of the frequency as well [87], and can be formulated as follows:
\[
Y_{\text{bus}}(\omega) = \begin{bmatrix}
Y_{11}(\omega) & \cdots & Y_{1N}(\omega) \\
\vdots & \ddots & \vdots \\
Y_{N1}(\omega) & \cdots & Y_{NN}(\omega)
\end{bmatrix},
\] (2.6)

where \(Y_{nm}(\omega)\) is the line admittance between buses \(n\) and \(m\).

### 2.2.3 Load Model

Since system frequency and bus voltages depend on the supply-demand power balance, the active and reactive ratings of loads are variables to be found as well, as described in [87–89], and formulated as follows:

\[
P_{Lk} = P_{Lko} \cdot \left(\frac{V_k}{V_o}\right)^{\alpha} \cdot (1 + K_p \cdot (\omega - \omega_o)),
\] (2.7)

\[
Q_{Lk} = Q_{Lko} \cdot \left(\frac{V_k}{V_o}\right)^{\beta} \cdot (1 + K_q \cdot (\omega - \omega_o)),
\] (2.8)

where \(P_{Lko}\) and \(Q_{Lko}\) are the active and reactive power of the load at nominal voltage and system frequency; \((\omega - \omega_o)\) is the frequency deviation; \(K_p\) and \(K_q\) are the parameters for the sensitivity of the loads to the frequency deviation; and \(\alpha\) and \(\beta\) are the exponent values determined by the type of the load [88,89], as expressed in Table 2.1.

<table>
<thead>
<tr>
<th>Load Type</th>
<th>(\alpha)</th>
<th>(\beta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant power (KP)</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Constant current (KC)</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Constant impedance (KI)</td>
<td>2.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Residential (R)</td>
<td>0.92</td>
<td>4.04</td>
</tr>
<tr>
<td>Commercial (C)</td>
<td>1.51</td>
<td>3.40</td>
</tr>
<tr>
<td>Industrial (I)</td>
<td>0.18</td>
<td>6.00</td>
</tr>
<tr>
<td>Typical (T)</td>
<td>0.92</td>
<td>1.00</td>
</tr>
</tbody>
</table>

### 2.2.4 Whole system model

Classic droop control is the most common primary level strategy for distributed generators in islanded microgrids. In traditional power systems, DGs are typically modeled as P-V (constant power and voltage) buses. In islanded microgrids, dispatchable DGs are typically modeled as droop buses, where the supplied active and reactive powers are not fixed and depend on the total power demand of the system and their power capacities. Finding these output powers is a crucial part of the solution of the algorithm. Assuming that the DG is connected to the system through a typical inductive output impedance (a transformer or filter inductor), the active and reactive powers can be decoupled and expressed with the following droop equations [87]:
\[ \omega = \omega_{\text{max}} - m_{\text{DG}} \cdot P_{\text{DG}}, \]  
\[ V = V_{\text{max}} - n_{\text{DG}} \cdot Q_{\text{DG}}, \]

where \( \omega_{\text{max}} \) and \( V_{\text{max}} \) are the maximum frequency and bus voltage of the microgrid, \( P_{\text{DG}} \) and \( Q_{\text{DG}} \) are the active and reactive powers injected by the DG, and \( m_{\text{DG}} \) and \( n_{\text{DG}} \) are the droop coefficients, computed from the power capacities, as follows:

\[ m_{\text{DG}} = \frac{\omega_{\text{max}} - \omega_{\text{min}}}{P_{\text{cap}}}, \]  
\[ n_{\text{DG}} = \frac{V_{\text{max}} - V_{\text{min}}}{Q_{\text{cap}}}, \]

where \( \omega_{\text{min}} \) and \( V_{\text{min}} \) are the minimum frequency and voltage of the microgrid and \( P_{\text{cap}} \) and \( Q_{\text{cap}} \) are the active and reactive power capacities of the DG.

![Topology of the RES-BESS unit](image)

**Figure 2.2:** Topology of the RES-BESS unit

### 2.3 Power Flow Algorithm

With the constantly increasing interest on microgrid research, some algorithms have been developed to solve the power flow of islanded microgrids with droop-based primary level controllers of DGs. As stated in [90], these can be classified in three different types: backward/forward sweep [91], Newton-types [92], and fixed-point types [89]. In this work, a power flow algorithm of the fixed-point type, and based on the Gauss-Seidel power flow algorithm, is presented. It is also based on the approach developed in [81]. Moreover, based on the model proposed in [34] and [46], an improved mathematical model describing a generation unit composed by a photo-voltaic system and a battery energy storage system can be formulated and included in the algorithm as an active generation unit.

The presented algorithm is based on the well known Gauss-Seidel iterative power flow algorithm; however, for the reasons mentioned before, islanded microgrids require a slightly different approach.
Summarizing, the variables to be found are listed in Table 2.2.

<table>
<thead>
<tr>
<th>Variables of</th>
<th>Unknown variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>System</td>
<td>$Y_{\text{matrix}}$, $\text{Frequency}$, $P_{\text{loss}}$</td>
</tr>
<tr>
<td>Loads</td>
<td>$V_{\text{bus}}$, $P_{\text{Load}}$, $Q_{\text{Load}}$</td>
</tr>
<tr>
<td>DGs</td>
<td>$V_{\text{bus}}$, $P_{\text{DG}}$, $Q_{\text{DG}}$</td>
</tr>
</tbody>
</table>

requires the absence of a slack bus and the variability of bus voltages and frequency system requires . System frequency is also a variable to be found, so are the active power of loads, the DERs and the losses of the Microgrid.

### 2.3.1 Types of Buses

Buses with dispatchable DGs are modeled as droop-based units [89]. Therefore, active and reactive powers of these buses are computed using equations (2.9) and (2.10).

The active and reactive powers of buses with loads are computed using equations (2.7) and (2.8), as functions of the system frequency and bus voltage.

Buses with RES-BESSs units are modeled with grid forming inverters. Using the aforementioned adaptive form of droop control, the active and reactive powers are computed using equations (2.2) and (2.3), as functions of the BESS SoC and the frequency of the system.

The variables to find are the system frequency, the power loss, the active and reactive powers of all buses, and the voltage magnitudes and angles of all the buses.

### 2.3.2 Power Flow Algorithm

The proposed power flow algorithm for islanded microgrids is described as follows, where $i$ is the iteration index:

- Step 1. Initialize the system frequency, and bus voltage magnitudes and phase angles. Initialize the convergence error $\epsilon_{\text{limit}}$.
- Step 2. Compute the initial admittance matrix $Y_{\text{bus}}(\omega)$, as a function of the system frequency bus voltages.

Step 3 and 4 are executed for all buses in a loop while $k \leq N$, where $N$ is the number of buses in the microgrid.

- Step 3. For bus $k$ in the system, compute the active and reactive power $P_k^{i+1}$ and $Q_k^{i+1}$ for iteration $i + 1$, according to the bus type:

  If bus $k$ is a Load:
2.3. POWER FLOW ALGORITHM

\[ P_{Lk}^{i+1} = P_{Lko} \cdot \left( \frac{V_i}{V_o} \right)^{\alpha} \cdot (1 + K_p \cdot (\omega^i - \omega_o)), \]  
(2.13)

\[ Q_{Lk}^{i+1} = Q_{Lko} \cdot \left( \frac{V_i}{V_o} \right)^{\beta} \cdot (1 + K_q \cdot (\omega^i - \omega_o)). \]  
(2.14)

If bus \( k \) is a DG:

\[ P_{Gk}^{i+1} = \frac{1}{m_{pk}} \cdot (\omega_{max} - \omega^i), \]  
(2.15)

\[ Q_{Gk}^{i+1} = \frac{1}{n_{qk}} \cdot (V_{max} - V_k^i). \]  
(2.16)

If bus \( k \) is a RES-BESS unit:

\[ P_{RBk}^{i+1} = P_{PVk} + \frac{1}{m_{RBk}} \cdot (\omega_{max} - \omega^i), \]  
(2.17)

\[ Q_{RBk}^{i+1} = \frac{1}{n_{RBk}} \cdot (V_{max} - V_k^i). \]  
(2.18)

If any computed power exceeds its limit, which is determined by the generation capacity or the rated power of the inverters, it must be set to its limit.

- Step 4. For bus \( k \) in the system, compute the bus voltage \( V_k^{i+1} \) for iteration \( i + 1 \):

\[ V_k^{i+1} = \frac{1}{Y_{kk}} \cdot \left[ P_k - jQ_k \right]_{\text{conj}} - \sum_{n=1}^{N} (Y_{kn} V_n^i) \].  
(2.19)

- Step 5. Increase \( k \) and go back to Step 3 until all \( N \) buses of the system have been computed.

- Step 6. Once all \( N \) buses have been explored, compute the system power loss for iteration \( i + 1 \):

\[ (S^{TotLoss})^{i+1} = \sum_{k=1}^{N} \sum_{n=1}^{N} -Y_{k,n} (V_k^i - V_n^i)^2, \]  
(2.20)

where \( V_k^i \) and \( V_n^i \) are the bus voltages, and \( Y_{k,n} \) is the line admittance from bus \( k \) to bus \( n \), at iteration \( i \).

- Step 7. Calculate the power requirement of the system using all loads, the power loss of the system, and the total power generated by the RES-BESS units. The power requirement needs to be generated by the dispatchable DGs.

\[ (P^{TotLoads})^{i+1} + (P^{TotLoss})^{i+1} - (P^{TotRB})^{i+1} = \sum_{k=1}^{N_{\text{dispGen}}} \frac{1}{m_{pk}} \cdot (\omega_{max} - \omega^i), \]  
(2.21)

where \( P^{TotLoads} \) is the total active load of the system, \( P^{TotLoss} \) is the total active power loss of the system, and \( P^{TotRB} \) is the total active power generated by the RES-BESS units.
Step 8. Using the power requirement, the system frequency for the next iteration can be computed using all available dispatchable DGs in the system, as follows:

$$\omega_{i+1} = \sum_{k=1}^{N_{dispGen}} \frac{1}{m_{pk}} \omega_{max} - \left((P_{TotLoads})_i^i + (P_{TotLoss})_i^i - (P_{TotRB})_i^i\right) \sum_{k=1}^{N_{dispGen}} \frac{1}{m_{pk}}. \quad (2.22)$$

Step 9. Compute the new convergence $\epsilon$ using the absolute rate of change of the system frequency and bus voltages; decide if it is small enough to break the loop:

$$\epsilon_{i+1} = |\omega_{i+1} - \omega_i| + \sum_{k=1}^{N} |V_{i+1}^k - V_i^k|. \quad (2.23)$$

If $\epsilon$ is above the threshold value $\epsilon_{limit}$ go back to Step 2; otherwise break the loop and attain the solution.

### 2.4 Simulation Results

The presented algorithm is tested on a 6 bus islanded microgrid, composed by two loads, two RES-BESS units, and one dispatchable DG. The simulation is conducted on a 48 hour typical load profile, in order to observe the SoC of the BESSs behavior. Figure 2.4 shows the topology of the islanded microgrid in this study. The power generated by the photo-voltaic systems is selected based on real-world solar system generation profiles. The SoC of the BESSs is intentionally selected at different depletion levels in order to prove the convergence of the model. Table 2.3 shows the capacity of generation units, while Table 2.4 describes the parameters of the transmission lines of the test system.

**Table 2.3:** Instant power generation capacities.

<table>
<thead>
<tr>
<th>Bus</th>
<th>DG(KW)</th>
<th>PV(KW)</th>
<th>BESS(KW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>–</td>
<td>4.0</td>
<td>7.0</td>
</tr>
<tr>
<td>5</td>
<td>5.0</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>6</td>
<td>–</td>
<td>4.0</td>
<td>6.0</td>
</tr>
</tbody>
</table>

**Table 2.4:** Line parameters.

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>R(Ω)</th>
<th>X(mH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>0.43</td>
<td>0.318</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0.15</td>
<td>1.843</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.3</td>
<td>0.35</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>0.2</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Figure 2.5 a) shows that, when the photo-voltaic systems are at their maximum power generation, the microgrid has sufficient power to supply the loads and charge the batteries. At night, when the photo-voltaic systems do not produce any power, the DG and the BESS supply the loads and maintain the supply-demand balance.
2.4. SIMULATION RESULTS

Figure 2.3: Power flow algorithm for AC islanded microgrids.

Figure 2.5 b) shows that bus voltages are always maintained within the ±5% limits. In Figure 2.5 c) it is shown that the system frequency is maintained within the ±1Hz boundaries, as considered in the droop functions. Figure 2.5 d) shows that, even when the batteries start with different depletion levels, their SoC converge over time. This is achieved by the inclusion of the SoC in the adaptive power dispatch droop function. Also, they show an equal number of charging and discharging stages,
equalizing their life expectancy in the long run.

2.5 Interim Conclusion

With the increasing penetration of distributed power sources into the power grid, the concept of microgrid has gained popularity in recent years. The electricity network is being gradually reshaped into a more flexible and inclusive system with a mix of distributed power generators, where end-users play a more conscious role in the supply-demand balance. The DGs are considerably smaller than those in the large scale power system, and inverter-based power sources have become the main structure of microgrids. However, power imbalances can happen frequently and unpredictably, due to time-varying weather conditions and load demands. Therefore, load shedding, energy curtailment and coupling/decoupling strategies are an integral part of microgrids for reliable power supply. Additionally, the use of battery systems can contribute to the resilience of microgrids, which can overcome the intermittent power generation levels of renewable energy sources. In order to study this emerging field, new control techniques, analysis tools and models need to be developed. Centralized and decentralized control architectures that have been proposed need in-depth investigations, each of which have their own benefits and drawbacks. Hierarchical control models, taking advantage of both approaches, need to be studied to propose a novel integrated feasible solution to the proportional load sharing and voltage and frequency restoration. Load shedding and coupling strategies have also been widely proposed as self-healing strategies are worth further investigating for improvement in the hierarchical control model. Future work may also involve dynamic model development for microgrids, especially in islanded
2.5. INTERIM CONCLUSION

Figure 2.5: Simulation results.
operation mode. Based on the developed model, a comprehensive small signal stability analysis can be performed, with new control methodologies to be proposed thereafter.
Chapter 3

A Fully Decentralized Adaptive Droop Optimization Strategy for Power Loss Minimization in Microgrids with PV-BESS

ABSTRACT

In this chapter, a fully decentralized adaptive droop optimization strategy for inverters is proposed for minimizing power loss during power transmission in islanded microgrids integrated with solar PV systems. From a hierarchical point of view, the proposed control architecture of the DGs encompasses both the primary and secondary levels, in a decentralized plug-and-play manner. The primary level, realized by a droop controller, is in charge of the fast response in load-sharing among all the generation units in the microgrid. The secondary level control, with a larger operation time scale, has the objective of minimizing the power loss in the system, which is achieved by the proposed adaptive droop functions. The advantage of the proposed droop optimization strategy is that the power generation units are fully decentralized by using only local measurements. The adaptability of the droop functions is achieved by adopting a P&O method. Particularly, when a small perturbation in the offset of the $P - f$ droop functions is introduced, the resultant effects on frequency and generated power are examined in order to select the offsets with the minimum power generation, indicating that the power loss is minimum. The P&O process is performed iteratively by every participating generation unit with a fixed perturbation over a constant time-step. Eventually, the system converges to a steady state with minimum power loss. The process within the secondary controller continues indefinitely and any change in loads or grid configuration will bring the system to a new steady state with minimum power loss.

The content of this chapter is mainly based on and modified from the following publications:

CHAPTER 3. A FULLY DECENTRALIZED ADAPTIVE DROOP OPTIMIZATION STRATEGY FOR POWER LOSS MINIMIZATION IN MICROGRIDS WITH PV-BESS


AND


3.1 Introduction

The concept of Microgrid has gained significant popularity in recent years, which is able to provide topological and technological flexibility to facilitate the inclusion of different DERs [2]. Typically, the DGs in microgrids are fossil-fuel fired generators; however, due to the concern of unsustainability of these power plants and their negative effects on the environment, RES have been widely employed as a clean and inexhaustible alternative [3]. Among all RESs, PV systems have been widely implemented in microgrids as one of the most popular RES due to its flexibility and scalability. Since the power generation levels of the PV systems heavily rely on weather conditions, Battery Energy Storage Systems (BESS) have been introduced to cope with the intermittency of the PV power generation. Thus, the combined use of PV systems and BESS (PV+BESS) as a unit have become a current trend in which the drawbacks of the sole PV systems can be attenuated.

The control of microgrids faces more complex and concerning challenges than those of traditional grids in terms of system stability, supply-demand balance and power flow optimality. Different objectives can be addressed in this regard, e.g., generation cost minimization, power loss minimization, greenhouse gas emission minimization, battery life expectancy maximization, or any combination of these. For an islanded microgrid which is isolated from the main grid, all the loads must be supplied by the DERs from inside the system, which poses a more pressing need of maintaining the voltage and frequency stability and minimizing power loss in the transmission lines. In this mode, the lack of an ”infinite capacity” generator, i.e., a slack bus, makes necessary that all the DGs contribute to the supply-demand power balance. To achieve this, droop schemes are the most common control technique in the primary control category for DGs. This method has been widely implemented due to its simplicity and robustness. The main advantage of this control is that it does not require a communication system to achieve proportional load-sharing, since the microgrid frequency and bus voltages can provide sufficient information for computing the power dispatch of each DG [1,3,9]. In the particular case of microgrids with decentralized controllers, voltage controllers have been studied for stability purposes in [93,94]. On the other hand, the study of PV-BESS power units in islanded microgrids with decentralized control has been widely explored in recent years [34–36,38]. Since the power generated by the PV system is intermittent and uncontrollable, the main objective of the PV-BESS control schemes is to manage the power supplied or absorbed by the BESS, using local measurements of voltage, current and frequency. To achieve this control purpose, adaptive droop
relations that use these local data and their batteries’ SoC have been proposed and widely embedded in the control schemes within their grid-interfaced DC-AC converters [33, 86].

Also, the optimization problem for droop-based islanded microgrids has been partially addressed in recent years, typically with the objective of reducing the operational costs of the DGs, e.g. fuel consumption [95]. The construction of linear and non-linear droop functions based on the power generation cost is presented in [25–28] in order to achieve the maximum economic benefits. Nevertheless, the optimization of generation cost will not necessarily minimize the power loss, since reaching the most economical solution of the microgrid could lead to a less efficient (in terms of power loss) but cheaper configuration of power system economic dispatch. For instance, a coal generator located far from the loads may be the cheapest power source within a microgrid, which however could be the one that produces most power loss because of the long transmission distance. In the particular case of inverter-based microgrids with high penetration of renewable sources, the optimization problem naturally presents other objectives, such as power loss minimization. In [29], non-linear functions are constructed to minimize the power loss in a microgrid, which however has the disadvantage of needing an off-line testing procedure for different load values. In [96] a decentralized approach for minimizing power loss in microgrids is presented, where the authors directly adjust the voltage levels of the inverters, posing the lack of practicality of the method. Since the approach we are presenting in this chapter differs from all previously presented optimization techniques, especially regarding the fully distributed architecture vs a typical centralized one, a direct comparison is impossible to make.

In this chapter, a fully decentralized adaptive droop optimization strategy for inverters is proposed for minimizing power loss in islanded microgrids integrated with PV-BESS. Fig. 3.1 shows the overall structure of the studied microgrid, where the each generation unit does not have access to the size and configuration of the microgrid. From a hierarchical point of view, the proposed control architecture of the DGs encompasses both the primary and secondary levels, in a decentralized plug-and-play manner. The primary level, realized by a droop control scheme, is in charge of the fast response in load-sharing among all the units in a microgrid [9, 10, 21]. The secondary level, with a larger operation time scale, has the objective of minimizing the power loss in the system, which is achieved by the proposed adaptive droop functions. The advantage of the proposed droop optimization strategy is that the power generation units are fully decentralized by using only local measurements (frequency and bus voltages),

![Figure 3.1: Generation unit unaware of the size, demand and topology of the microgrid.](image-url)
which significantly reduces or completely eliminate the need of having advanced communication channels in microgrids for control purposes. The adaptability of the droop coefficients is achieved by adopting a P&O method, as commonly used in MPPT mechanisms. The proposed decentralized loss minimization technique is able to adaptively manipulate the droop of DGs to suit any changes in loads, generator sizes, transmission line specifications. When there is a disturbance in the microgrid, the proposed method is capable of actively changing the droop so that the microgrid system will settle to a new steady state with minimized power loss. The proposed loss minimization strategy is easy to implement and does not require data communication among DGs and loads, posing its high applicability in real-world applications.

The remainder of the chapter is organized as follows. In Section 3.2 the basic description of the decentralized primary controller for the generation units is briefly presented, making emphasis on the high level power controller. The secondary controller and the power loss minimization strategy are detailed in Section 3.3. In Section 3.4, an overall power flow algorithm for loss minimization is detailed. Section 3.5 presents three case studies with simulation results, proving the functionality of the optimization strategy. Finally, a conclusion is drawn in Section 5.5.

Figure 3.2 shows the details of where this work is located according to the classification frame adopted in this thesis.

3.2 Primary Droop Control

3.2.1 Inverter Model

In this section, the mathematical model of the primary control level of generation units in a microgrid is presented. In this study, a control loop for the generation unit AC/DC converters is adopted from [97].
3.2 PRIMARY DROOP CONTROL

The control schematic of such inverter is illustrated in Fig. 3.3, which comprises three stages in different levels: power, voltage and current controllers.

![Control schematic of inverter](image)

**Figure 3.3:** Structure of the inverter model.

### 3.2.2 Droop-based Power Controller

Using the measurements from the output filter of the inverter, the power controller of the inverter control structure generates voltage and frequency references using the $P-f$ and $V-Q$ droop functions. As shown in Fig. 3.3 the instantaneous active and reactive power ($\tilde{p}_o$ and $\tilde{q}_o$) are obtained with the measured output voltage and current $v_{o}^{dq},i_{o}^{dq}$. After passing through a low pass filter with cut-off frequency $\omega_c$, the fundamental components of real and reactive power $P_o$ and $Q_o$ can be obtained from the following equations [97]:

\begin{align}
\tilde{p}_o &= i_o^d v_o^d + i_o^q v_o^q, \\
\tilde{q}_o &= i_o^d v_o^q - i_o^q v_o^d, \quad (3.1)
\end{align}

\begin{align}
\frac{dP_o}{dt} &= \omega_c (\tilde{p}_o - P_o), \\
\frac{dQ_o}{dt} &= \omega_c (\tilde{q}_o - Q_o). \quad (3.2)
\end{align}

The droop control is a well-known strategy used in power controller for inverters in microgrids for ensuring load sharing. The idea behind this concept is to simulate the behavior of synchronous generators, changing the injected power in function of the power demand and frequency and voltage droops. As a result, the frequency and voltage references of the inverter increases/decreases when there is a change in the power demand on the droop equations and the voltage phase angle is set by integrating the frequency as stated in the following equations,

\begin{align}
f &= f^{\text{nom}} - m \cdot P_o, \quad (3.3)
\end{align}

\begin{align}
v_o^d &= V^{\text{nom}} - n \cdot Q_o, \\
v_o^q &= 0, \quad (3.4)
\end{align}

\begin{align}
\dot{\theta} &= f, \quad (3.5)
\end{align}

where $f$ is the inverter frequency, $f^{\text{nom}}$ and $V^{\text{nom}}$ are the nominal frequency and voltage (at no-load state) state, and $m$ and $n$ are the coefficients in the $P-f$ and $Q-V$ droop functions.
3.3 Proposed Decentralized Secondary Control for Power Loss Minimization

The primary level droop controllers of the inverters are in charge of maintaining the balance between power generation and consumption. However, in order to address the power loss minimization problem, a secondary level controller is implemented. Secondary level controllers in islanded microgrids have been typically used for frequency and/or voltage restoration [22]. This is usually achieved by injecting an offset in the droop functions in order to reach an equilibrium point where \( f_{sys} = f_{nom} \) and \( V_{bus} = V_{nom} \). However, in this study the objective of the secondary level controller is to minimize the power loss, while maintaining the frequency and bus voltages within an acceptable range of deviation (±1Hz for frequency and ±5% for voltage).

Since solar PV systems usually function with an MPPT control, each of the PV generation unit has a BESS in this study, which makes them suitable for working as a dispatchable power inverter with a droop control. Thus, from a microgrid perspective, the power supplied by the generation unit \( k \) in this study can be expressed as,

\[
P_{Gen_k} = P_{PV_k} + P_{BESS_k},
\]

where \( P_{PV_k} \) is the power generated by the PV solar system and \( P_{BESS_k} \) is the power supplied/absorbed by the BESS. Since the generation unit at its power level is ruled by its droop function, and \( P_{PV_k} \) is uncertain and non-dispatchable, \( P_{BESS_k} \) can be expressed as follows,

\[
P_{Gen_k} = P_{PV_k} + \eta_k \cdot \frac{f_{nom} \cdot f_{sys}}{m_k},
\]

where \( \eta_k \) is the overall charging/discharging efficiency of the BESS (0.9 in this study) [98]. Note that \( P_{BESS_k} \) is positive when injecting power (discharging) and negative when absorbing power (charging).

The primary level of the generation units guarantee that the power balance within the microgrid is always satisfied (as long as the generated power does not exceed the total generation capacity), i.e.,

\[
\sum_{k=1}^{L} P_{Gen_k} = \sum_{j=1}^{M} P_{Load_j} + \sum_{r=1}^{N} P_{Loss_r},
\]
3.3. PROPOSED DECENTRALIZED SECONDARY CONTROL FOR POWER LOSS MINIMIZATION

where \( P_{\text{Gen}_k} \) is the active power supplied by the generation unit \( k \), \( P_{\text{Load}_j} \) is the active power absorbed by the load \( j \) and \( P_{\text{Loss}_r} \) is the active power dissipated by the transmission line \( r \); \( L \) is the number of generation units, \( M \) is the number of load buses and \( N \) is the number of transmission lines.

3.3.1 Load and Power Loss Profiles

The idea underpinning the construction of this secondary controller is based on the conceptualization of a Load + Loss profile (blue line), which is shown in Fig. 3.5, where \( f_{\text{max}} \) and \( f_{\text{min}} \) stand for the maximum deviation of the system frequency, which is set \( 50 \pm 1 \) Hz (\( f_{\text{max}} = 51 \) Hz and \( f_{\text{max}} = 49 \) Hz) in this study according to the frequency operating standards by AEMO [99]. Term \( f_{\text{sys}} \) stands for the steady state system frequency. The range described by arrows means that the droop functions are shifting due to the proposed P&O strategy. However, regardless of the changes in the deviation limits, system frequency is always kept within \( \pm 1 \)Hz range of the nominal value. By incorporating an offset \( \Delta f_{\text{step}} \) in the droop function, the generated power of this unit changes to account for the corresponding part of the Load + Loss profile. Once an offset in the droop function of a Generation Unit is incorporated, the microgrid will reach a new steady-state frequency, with all generation units having an updated share of Load + Loss. Since the load is assumed constant in this study, the curvature in Load + Loss profile, if any, indicates a change in the power loss in the Microgrid. Based on the trajectory of the curvature, an increase or decrease of power loss can be detected, which determines the direction of the perturbation at the next operation time step. Therefore, the closest point to the load profile represents the point with minimum power loss.

3.3.2 Perturbation Step

In the proposed strategy, the perturbation step is a fixed offset (\( \Delta f_{\text{step}} \)) in the droop function of a generation unit, in order to produce a change in the output power of this unit. After the offset is introduced, the whole system reaches a new steady-state frequency, and the new power level supplied
by this perturbed generation unit $k$ with the injected fixed offset $\Delta f_{\text{step}}$ can be expressed as follows,

$$P'_k = \frac{f^\text{nom}_k + \Delta f_{\text{step}} - f_{\text{sys}}}{m_k}. \quad (3.9)$$

### 3.3.3 Observation and Decision-Making Procedures

Since the size, load and topology of the microgrid is unknown for each generation unit, and there is no communication among them, it is impossible to discern if the new generated power level of the perturbed unit corresponds to the generation-demand power balance or a change in the power loss; however, by examining the normalized frequency and active power rates of change, once the perturbation step has been applied it is possible to identify the direction ($\Delta f_{\text{step}}$ positive or negative) towards which the secondary controller continues searching for the optimal offset.

![Figure 3.6: Conceptual illustration of the adaptation procedure of a generation unit.](image)

Fig. 3.6 shows graphically the process of introducing the perturbations in the droop function of a generation unit, where the numbers 1, 2 and 3 represent the starting point and the first and second perturbation steps, respectively. The black arrows show how the proposed strategy is chronologically implemented, going from 1 to 3.

From Fig. 3.5, it can be seen that under the assumption that total load is constant (red line), the curvature of the Load + Loss profile (blue line) represents the change in power loss. Thus, the closest point of the Load + Loss profile to the Load profile represents the point where the power loss is minimum, which is located in the “knee” of the curve. Since the curve is impossible to predict or estimate, the objective of the proposed strategy is to explore the function and approach as close as possible to this point in the curve.

In order to control the adaptation sequences of the generation units, a real-time counter is embedded within the controller, with the objective of governing the adaptation procedures. Fig. 3.7 demonstrates the flowchart of the control algorithm, where $T_{\text{count}}$ is the real-time counter and $T_{\text{adapt}}$ is the control time span that controls the execution of the adaptation procedure. Fig. 3.8 shows the control sequences over time, where is $\Delta t$ is the time step of the secondary controller and $\Delta T$ is the complete adaptation procedure time span.
Hereafter, we provide the mathematical proof for the proposed P&O seeking algorithm, starting with a small nominal frequency $f_{\text{nom}}$, i.e., the optimal nominal frequency is higher than the initial nominal frequency. Based on the above discussions and assuming $n$ identical generation units, we can formulate the power loss of the microgrid in discrete time (at $j$th iteration) as

\[
P_{\text{loss}}(j\Delta t) = P_{\text{gen}}(j\Delta t) - P_{\text{load}} = \frac{n}{m} \left( f_{\text{nom}}((j-1)\Delta t)+u(j\Delta t)-f_{\text{sys}}(j\Delta t) \right) - P_{\text{load}},
\]

where $u(j\Delta t)$ is the droop function perturbation and $u(t) \in \{-\Delta f_{\text{step}}, \Delta f_{\text{step}}\}, \forall t \geq 0$. Therefore, we can have the derivative of power loss in the following form,

\[
\frac{dP_{\text{loss}}(t)}{dt} = \frac{P_{\text{loss}}((j+1)\Delta t) - P_{\text{loss}}(j\Delta t)}{\Delta t} = \frac{n}{m\Delta t} \left[ \left( f_{\text{nom}}(j\Delta t)+u((j+1)\Delta t)-f_{\text{sys}}((j+1)\Delta t) \right) - \left( f_{\text{nom}}((j-1)\Delta t)+u(j\Delta t)-f_{\text{sys}}(j\Delta t) \right) \right].
\]
Figure 3.8: Control sequences of the control algorithms of the distributed inverters in the studied microgrid.

Apparently $f_{\text{nom}}^\text{Power}((j\Delta t) + u(j\Delta t)$, if we introduce a $g(t, u)$ to denote the derivative of power loss, then (3.10) can be simplified as

$$g(t, u) = -\frac{dP_{\text{loss}}(t)}{dt} = -\frac{n}{m\Delta t} \left[ u((j + 1)\Delta t) - f_{\text{sys}}((j + 1)\Delta t) \right] + f_{\text{sys}}(j\Delta t)),$$

where the negative sign ‘−’ is for the convenience of providing the proof. Now we provide the expression for the perturbation variable $u(j\Delta t)$ as follows, assuming the initial nominal frequency $f_{\text{ini}}^\text{nom}$ is a small value, i.e., below the optimal nominal frequency,

$$u(0) = \Delta f_{\text{step}}, u(j\Delta t) = u((j-1)\Delta t), \text{ if } P_{\text{loss}}(j\Delta t) < P_{\text{loss}}((j-1)\Delta t), u(j\Delta t) = S[u((j-1)\Delta t)], \text{ otherwise},$$

where the switching function $S[\cdot]$ is defined as

$$S[\Delta f_{\text{step}}] = -\Delta f_{\text{step}}, \quad S[-\Delta f_{\text{step}}] = \Delta f_{\text{step}}.$$

In this study, we have the following assumption,

**Assumption 3.3.1.** In this study, for two consecutive time steps, the system frequency does not change substantially, and the perturbed frequency in the droop function is thus always greater than this change, i.e.,

$$\Delta f_{\text{step}} > |f_{\text{sys}}((j + 1)\Delta t) - f_{\text{sys}}(j\Delta t)| \geq 0$$

**Lemma 3.3.1.** Based on Assumption 3.3.1 and (3.10), we can have

$$l g(t, -\Delta f_{\text{step}}) > 0, \quad g(t, \Delta f_{\text{step}}) < 0.$$  

**Assumption 3.3.2.** Assume there exists the minimum power loss in the microgrid of interest, denoted as $P_{\text{loss}}^\text{min}$, which is introduced for proving the theory, but is unknown while performing the proposed P&O process.

**Assumption 3.3.2** is apparently valid for all physical electric network. Then the goal of the proposed power loss minimization strategy is to make $P_{\text{loss}}(t)$ as close as possible to $P_{\text{loss}}^\text{min}$. We define the steady state error $e_{\text{ss}}(\Delta t)$ as follows,

$$e_{\text{ss}}(\Delta t) = \lim_{t_0 \to t_0} \sup_{t \geq t_0} |P_{\text{loss}}(t) - P_{\text{loss}}^\text{min}|.$$
Proposition 3.3.1. With Assumption 3.3.1, Assumption 3.3.2 and Lemma 4.3.1, the steady state error (3.13) satisfies

$$\lim_{\Delta t \to 0} e_{ss}(\Delta t) = 0.$$  (3.14)

Proof of Proposition 3.3.1: Since the function $P_{loss}(t)$ is continuous, and bounded and closed, it follows from Assumption 3.3.1 and Lemma 4.3.1 that there exist constants $D > \epsilon_0 > 0$ such that

$$D \geq g(t, -\Delta f_{step}) \geq \epsilon_0, \quad -D \leq g(t, \Delta f_{step}) \leq -\epsilon_0,$$

which implies that given that $f_{\text{nom}}^{\text{ini}}$ is a small value, $P_{loss}$ is always decreasing, i.e., when $u(t) = \Delta f_{step}$ and it is always increasing when $u(t) = -\Delta f_{step}$. Furthermore, (3.15) implies that

$$P_{loss}(t + \Delta t, u(\tau)) \leq P_{loss}(t) - \epsilon_0 \Delta t,$$

if $u(\tau) = \Delta f_{step} \quad \forall \tau \in [t, t + \Delta t)$,

$$P_{loss}(t + \Delta t, u(\tau)) \geq P_{loss}(t) + \epsilon_0 \Delta t,$$

if $u(\tau) = -\Delta f_{step} \quad \forall \tau \in [t, t + \Delta t)$.

Moreover, it also follows from (3.15) that

$$P_{loss}(t) - D \Delta t \leq P_{loss}(t + \Delta t) \leq P_{loss}(t) + D \Delta t,$$

if $u(\tau) \in \{-\Delta f_{step}, \Delta f_{step}\}$.

$\forall \tau \in [t, t + \Delta t)$. Now it follows from the equations (3.10), (3.15) and (3.15) that the perturbation frequency (3.10) steers the $P_{loss}(t)$ to the interval $[P_{loss}^{\text{min}} - D \Delta t, P_{loss}^{\text{min}} + D \Delta t]$ and keeps it in this interval. Therefore, $e_{ss}(\Delta t) \leq D \Delta t$. This obviously infers (3.14) and completes the proof of Proposition 3.3.1. The “knee” point in the Load + Loss profile reflects a sign change in the derivative of $P_{load} + P_{loss}$. Since load demand is assumed constant in this study, but unknown, the “knee” is the point where $\frac{dP_{loss}(t)}{dt}$ starts changing signs, which thus indicates that the lowest power loss has been reached. Similar rationale can be applied to proving a large initial nominal frequency, which is omitted in this work.

Corollary 3.3.1. Based on the above proof, the proposed P&O process is executed indefinitely and eventually all the participating units reach the droops that represent the minimum power loss for the overall system. The final power loss is kept within a small range $[P_{loss}^{\text{min}} - D \Delta t, P_{loss}^{\text{min}} + D \Delta t]$. Once the droops of all generation units reach the values that lead to minimum power loss for the entire power system, the droops will keep perturbing back and forth within a small vicinity, i.e., lingering around the “knee point” until there is a change in loads or grid configuration, which will make the droop-seeking algorithm re-start and the system will reach and settle at a new steady state with minimum power loss over time.

3.4 Overall Optimal Power Flow Algorithm for Loss Minimization

Fig. 3.9, which is the combination of both power flow algorithm and the proposed loss minimization method, demonstrates the overall power flow algorithm for loss minimization employed in this study. The model at a power flow level is adopted and adapted from the classic Gauss-Seidel iterative method.
Note that the algorithm runs indefinitely, and any change in grid configuration or load demand will lead to another P&O procedure, thus a new steady state.

for autonomous microgrids with droop control [87,89]. Basic equations are shown as follows. For bus $k$ in the system, compute the voltage $V_k$:

$$V_k = \frac{1}{Y_{kk}} \cdot \left[ \frac{P_k - jQ_k}{(V_k)_{\text{conj}}} - \sum_{n=1}^{N} (Y_{kn}V_n) \right],$$

(3.15)
where \( Y_{bus} \) is the admittance matrix of the system. The power loss of the system is computed as:

\[
(S^{TotLoss}) = \sum_{k=1}^{N} \sum_{n=1}^{N} -Y_{k,n}(V_k - V_n)^2,
\]

where \( V_k \) and \( V_n \) are the bus voltages and \( Y_{k,n} \) is the line admittance from the bus \( k \) to the bus \( n \).

The system frequency can be calculated using the droops coefficients and the total generated power:

\[
f_{sys} = \frac{\sum_{k=1}^{L} \frac{1}{m_k} f_{nom}^k - (P_{TotLoads} + P_{Loss})}{\sum_{k=1}^{L} \frac{1}{m_k}}.
\]

3.5 Case Studies

![Microgrid topology](image)

**Figure 3.10:** Microgrid topology in this study

In order to test the functionality and feasibility of the proposed optimization strategy, an islanded
CHAPTER 3. A FULLY DECENTRALIZED ADAPTIVE DROOP OPTIMIZATION STRATEGY FOR POWER LOSS MINIMIZATION IN MICROGRIDS WITH PV-BESS

microgrid model developed in MATLAB coding environment is presented. The generation units are modeled with primary level droop controllers, where the droop coefficients are computed as functions of their power capacities. As stated before, the decentralized secondary controller is embedded within each inverter and their droops are adjusted at every adaptation time step. Fig. 3.10 shows the topology tested in this case study. The distribution line parameters are shown in TABLE 3.1.

Table 3.1: Line parameters

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>R (Ω)</th>
<th>X (mH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>0.63</td>
<td>0.318</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>0.5</td>
<td>0.35</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0.35</td>
<td>1.843</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>0.4</td>
<td>0.25</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>0.25</td>
<td>0.05</td>
</tr>
</tbody>
</table>

In this study, 3 distinct cases are incorporated to test the functionality of the proposed decentralized loss minimization algorithm. In case 1 and case 2, load at specified busbars vary over time, whereas in case 3 the topology of the microgrid changes and an additional connection is established. Through time-domain simulations, the functionality of the proposed control strategy is verified. The purpose of this study is to prove the optimization strategy, the time and perturbation frequency steps are selected sufficiently large to ensure the stability of the system, which are shown in TABLE 3.2.

Table 3.2: Secondary control parameters

<table>
<thead>
<tr>
<th>∆t</th>
<th>0.5s</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆f_{step}</td>
<td>0.01Hz</td>
</tr>
</tbody>
</table>

3.5.1 Case 1

The parameters of loads and generation units are shown in TABLE 3.3. The loads gradually change from $t = 400s$ to $t = 500s$ reaching a new steady state with the same load demand as when the simulation starts (load in bus 1 increases to 8.387 KW and 2.855 KVAR while load in bus 3 decreases to 4.223 KW and 1.007 KVAR). The PV solar system is generating the same amount of power for all units, and the BESSs hold the same energy storage level at the beginning of the simulation. Since generation unit in bus 6 is required to inject more power into the microgrid, the SoC of its BESS decreases, while BESS in bus 4 and 5 continue charging. Simulation results for case 1 are shown in Figs. 3.11 (a)∼(e), for active power generation, power loss, frequency of each inverter, busbar voltages and SoC of BESSs, respectively.

It can be seen that the system initially settles at around $t = 350s$ till $t = 400s$ when the load demands change in the microgrid. During $t = 350s$ ∼ 400s, there are small oscillations in Figs. 3.11 (a)∼(d), which are caused by the continuous droop-seeking procedures in all generation units, as explained in Remark 1. Similar phenomena can also be observed during $t ≥ 600s$ and also in the following cases.
3.5. CASE STUDIES

Figure 3.11: Simulation results in case 1.
### Table 3.3: Loads and generation units in Case 1 (kW, kVar)

<table>
<thead>
<tr>
<th>Bus</th>
<th>P(_{\text{Load}})</th>
<th>Q(_{\text{Load}})</th>
<th>Inverter Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.447 (\uparrow)</td>
<td>1.875 (\uparrow)</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>7.163 (\downarrow)</td>
<td>1.987 (\downarrow)</td>
<td>-</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>9</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>-</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 3.4: Loads and generation units in Case 2 (kW, kVar)

<table>
<thead>
<tr>
<th>Bus</th>
<th>P(_{\text{Load}})</th>
<th>Q(_{\text{Load}})</th>
<th>Inverter Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.435 (\uparrow)</td>
<td>1.548 (\uparrow)</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>6.842 (\downarrow)</td>
<td>2.204 (\downarrow)</td>
<td>-</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>-</td>
<td>10</td>
</tr>
</tbody>
</table>

#### 3.5.2 Case 2

The parameters of the loads and generation units for this case are shown in Table 3.4. The loads again gradually change from \(t = 400\) s to \(t = 500\) s reaching a new steady state. The power demands stay the same (load at bus 1 increases to 6.375 kW and 2.528 kVar, while load at bus 3 decreases to 3.902 kW and 1.224 kVar). The PV solar system is generating the same amount of power for each generation unit, and the BESSs hold the same energy storage level at the beginning of the simulation. Since generation unit in bus 5 is required to inject less power into the microgrid and the PV solar system is providing enough power for feeding the microgrid and charging the batteries, the SoC of its BESS increases much faster than the others. When the loads change, the active power injected in bus in bus 4 increases, and the power injected in bus 6 decreases, the rate of change of their SoCs decreases. Simulation results for case 2 are shown in Figs. 3.12 (a)\(~\)\(\sim\) (e), for active power generation, power loss, frequency of each inverter, busbar voltages and SoC of BESSs, respectively.

#### 3.5.3 Case 3

### Table 3.5: Loads and generation units in Case 3 (kW, kVar)

<table>
<thead>
<tr>
<th>Bus</th>
<th>P(_{\text{Load}})</th>
<th>Q(_{\text{Load}})</th>
<th>Inverter Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.435 (\uparrow)</td>
<td>1.548 (\uparrow)</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>2.015 (\uparrow)</td>
<td>0.705 (\uparrow)</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>5.851 (\downarrow)</td>
<td>2.003 (\downarrow)</td>
<td>-</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>-</td>
<td>10</td>
</tr>
</tbody>
</table>

In this case the topology changes and the load in bus 2 is connected. The parameters of the loads and generation units are shown in TABLE 3.5. Again, the loads change gradually from \(t = 400\) s to
Figure 3.12: Simulation results in case 2.
\( t = 500 \text{s} \) reaching a new steady state with higher load demands (load in bus 1 increases to 5.170 kW and 1.793 kVar, load in bus 2 increases to 3.485 kW and 1.195 kVar and load in bus 3 decreases to 4.381 kW and 1.513 kVar). The PV solar system is generating the same power level for each generation unit, and the BESSs hold the same energy storage level at the beginning of the simulation. Since generation unit in bus 6 is required to inject more power into the microgrid the SoC of its BESS decreases faster than the others. Simulation results for case 3 are shown in Figs. 3.13 (a)\( \sim \) (e), for active power generation, power loss and frequency of each inverter, respectively.

### 3.6 Interim Conclusion

In this study, we have proposed a novel secondary level control for power loss minimization in droop inverter-based islanded microgrids. The presented method operates in a fully decentralized manner, without any load or topology information, the proposed loss minimization strategy only requires local frequency and voltage measurements. Simulation results have demonstrated its capability of reducing microgrid power loss while maintaining the frequency and voltage stability, under various loading conditions and system topologies. However, the main drawback of this strategy is that relies on the blind exploration of unknown functions (Load + Loss profiles), where the performance deteriorates when the grid grows in complexity, such as in heavily meshed networks. In these scenarios, the effects of a change in a droop function does not produce big enough changes in the power generation levels to be clearly appreciated by the secondary controller, due to the high interdependency of the system. Therefore, the global minimum power loss may not be found. Additionally, while addressing the power loss minimization problem, other aspects of the microgrid are compromised, e.g., healthy and equal charging and discharging cycles for the BESS. Future studies in topic will include: 1) further studies on microgrid load and size characterization without communications, since exhaustive experiments showed that the scalability of the microgrid size can compromise the performance of the proposed algorithm; 2) including different types of generation units with different primary controllers; 3) a systematic methodology to find the global minimum loss; and 4) exploring alternatives for balancing power loss optimality and BESS management, since the proposed strategy may increase the batteries cycles and shorten life expectancy.
3.6. INTERIM CONCLUSION

Figure 3.13: Simulation results in case 3.
Chapter 4

Consensus-Based Distributed Control for Hybrid AC/DC Islanded Microgrid

ABSTRACT

In this chapter, a distributed control architecture for hybrid AC/DC islanded droop-based microgrids is proposed to address the most common cooperative objectives, including AC frequency and DC voltage restoration, BESSs charge/discharge coordination, proportional active power dispatch and ILC power flow control. Distributed control architectures for AC and DC microgrids have been studied in recent years as a way to address secondary and tertiary control objectives. Such architectures are implemented using low-bandwidth neighbor-to-neighbor communication networks known as multi-agent systems, where agents are located at different buses along the microgrid, depending on the control objectives. From a hierarchical point of view, the studied hybrid AC/DC islanded microgrid presented in this chapter is controlled by droop functions at its primary level. At the secondary level, the proposed distributed control architecture takes place. Agents gather and share local information, in order to reach a consensus, depending on the objective addressed. Once a consensus has been reached, agents located within dispatchable units will obtain new set-points for their primary level droop functions, bringing the system to a new steady state. Simulation results demonstrate the effectiveness of the proposed cooperative control at addressing the different objectives under changing loading levels.

The content of this chapter is mainly based on and modified from the following paper under revision:


4.1 Introduction

Due to the increasing penetration of renewable energy sources, the concept of microgrid is attracting the special attention of power systems researchers and engineers. Its technological versatility to facilitate
the inclusion of different DERs allows topological flexibility that can seamlessly incorporate AC and DC loads, generation units and power devices [2]. However, the control of microgrids encounters complex problems and challenges, not previously seen in traditional power systems [3]. In the particular case of islanded microgrids, the absence of a slack bus implies that balance and stability must be maintained by the contribution of DGs and power devices within the system. On top of that, the uncertainty of renewable energy sources further compromises the power supply capability of the generation units. Therefore, BESSs need to play an important role in maintaining the power supply and demand balance [33].

Hybrid AC/DC microgrids are composed of both AC and DC loads, energy sources, and power devices [100]. Nowadays, these hybrid power systems are considered the most feasible future topologies, accommodating a high penetration of distributed renewable energy sources [31]. Advantages and control challenges are naturally inherited from both AC and DC microgrids [101]. A hybrid microgrid can be integrated by multiple AC and DC sub-grids, interconnected by one or multiple ILCs [102]. To dynamically balance the varying power supply and load demand in islanded microgrids, droop-based controllers are typically employed to govern the DGs and BESSs power dispatch [1, 3, 9]. Also, droop functions that involve both AC sub-grid frequency and DC coupling bus voltage have been proposed as a fully distributed way of controlling the power flow in the ILC, while contributing to maintaining the power balance of the system [23, 32]. Regarding the secondary level control, distributed consensus-based approaches for AC and DC microgrids have been proposed, addressing a variety of objectives. These approaches rely on low-bandwidth communication networks, that allow the participating units (agents) to cooperate in a coordinated way in order to address global objectives while maintaining completely self-sufficient operation [77]. A review of distributed control for microgrids was presented in [76]. Specifically regarding AC microgrids, distributed voltage control and frequency restoration approaches have been proposed in [78, 103–105]. In [106], a consensus-based voltage stability and reactive power sharing control was presented. Also, a distributed hierarchical control for microgrid clusters was presented in [107]. Regarding DC microgrids, a distributed approach for voltage control and proportional load sharing was presented in [108]. The optimal dispatch problem in AC microgrids can also be addressed in a distributed way, as shown in [109–112]. Also, a distributed control for microgrids with paralleled generators was presented in [113]. Furthermore, the presence of time delays in a distributed approach for optimal management of microgrids was studied in [114]. Moreover, BESSs coordination is an objective that can be addressed through a distributed approach, as presented in [115]. Although all the previously cited papers proposed and proved the feasibility of distributed consensus algorithms in their specific case scenarios, none of them addressed the hybrid AC/DC microgrid. In this work, we present a consensus-based approach for hybrid AC/DC microgrids. Agents are distributed over the entire microgrid, gathering and sharing different local measurements, according to the objectives to be addressed. The main contributions of this work are highlighted as follows.

1. The consensus-based distributed architecture is implemented in a hybrid AC/DC microgrid, seamlessly allowing the participation and contribution of both AC and DC power devices.

2. The average DC voltage variable, obtained through a consensus algorithm, is used to improve the power flow control of the ILC.
3. Proportional active power dispatch for AC and DC generation units is achieved by means of a consensus algorithm.

4. The AC frequency and average DC voltage restoration objective is successfully achieved using a consensus algorithm.

5. AC and DC BESSs coordination is achieved by implementing a composed dispatch function that involves a consensus algorithm, the SoC, and local measurements.

The remainder of this chapter is organized as follows. In Section 4.2 the basic model of the hybrid AC/DC microgrid is presented, as well as a brief description of the droop controllers governing the power devices. In Section 4.3 the graph theory of the multi-agent system and the distributed ratio-consensus algorithm underpinning the posterior control algorithms are presented. In the four subsequent sections, we address the objectives previously mentioned, presenting for each of them a new consensus algorithm implementation and the corresponding simulation results. In Section 4.4, we realize the objective of improving the ILC power flow control using average DC bus voltage. In Section 4.5, the proposed proportional active power dispatch algorithm is presented. In Section 4.6, we address the AC sub-grid frequency and average DC bus voltage restoration. In Section 4.7 we address the BESSs charging/discharging coordination issues, considering they can be located on either side of the microgrid. A conclusion is drawn in Section 5.5.

Figure 4.1 shows the details of where this work is located according to the classification frame adopted in this thesis.
4.2 Hybrid AC/DC Microgrids

According to the classification proposed in [102], the general case we study in this chapter is considered to be an AC-DC coupled microgrid, with no dominant sub-grid. Both sub-grids consist of DGs with droop controllers and loads that fluctuate. A single bi-directional ILC with a droop function at its primary level control governs the power flowing from one sub-grid to the other. The power balance of the entire system is guaranteed by the primary droop controllers as long as the power demand does not exceed the power supply capacity and the power rating of ILC. The topology of the studied microgrid is presented in Fig. 4.2, as a general example of a hybrid AC/DC microgrid.

**Figure 4.2:** Topology of a general example of a hybrid AC/DC microgrid.

### 4.2.1 AC Sub-grid Droop Control

The droop control is a well-known strategy used in power controllers for dispatchable DGs in AC microgrids for ensuring proportional load sharing. The idea behind this concept is to simulate the behavior of synchronous generators, dynamically changing the generated power as a function of the power demand and frequency and voltage droops. The inner control loop references of current and voltage are calculated from the droop functions, as stated in the following equations,

\[
    f = f_{\text{max}} - m \cdot P_G, \tag{4.1}
\]

\[
    V_{AC} = V_{AC}^{\text{max}} - n \cdot Q_G, \tag{4.2}
\]

where \( f \) is the system frequency, \( V_{AC} \) is the voltage of the AC bus, \( f_{\text{nom}} \) and \( V_{AC}^{\text{nom}} \) are the nominal frequency and bus voltage (at no-load state), \( P_G \) and \( Q_G \) are the generated active and reactive powers, respectively, and \( m \) and \( n \) are the droop coefficients.

### 4.2.2 DC Sub-grid Droop Control

Similar to its AC counterpart, the DC droop control is widely used in power controllers for dispatchable DGs in DC microgrids. The basic idea is to dynamically adjust the generated power as a function of the
current demand and bus voltage droop. The DC bus voltage reference of the DG increases/decreases when there is a change in the current demand, according to the following equation,

$$V_{DC} = V_{DC}^{\text{nom}} - r \cdot I_G,$$

(4.3)

where $V_{DC}^{\text{nom}}$ is the nominal bus voltage, and $r$ is the droop coefficient, obtained from:

$$r = \frac{V_{DC}^{\text{max}} - V_{DC}^{\text{min}}}{I_{\text{max}}}.$$

(4.4)

Since $I_{\text{max}}$ is generated when $V_{DC} = V_{DC}^{\text{min}}$, and knowing that $P_{\text{max}} = I_{\text{max}} \cdot V_{DC}^{\text{min}}$, (4.3) can be reformatted as:

$$V_{DC} = V_{DC}^{\text{max}} - u \cdot P_G,$$

(4.5)

where $u$ is the droop coefficient, defined as a function of $P_{\text{max}}$, as follows,

$$u = \frac{V_{DC}^{\text{max}} - V_{DC}^{\text{min}}}{P_{\text{max}}}.$$

(4.6)

### 4.2.3 Interlinking Converter Droop Control

In hybrid AC/DC microgrids, the ILC controls the power flow between the AC and DC sub-grids. Droop functions governing the amount of power being converted have been proposed [23,32], as a fully distributed way of coping with loading fluctuations. Using only normalized local measurements of AC frequency and DC bus voltage, the ILC can estimate the loading levels of both sub-grids, and determine the direction and amount of active power to convert. The normalization equations are defined as follows,

$$\hat{f} = \frac{f - (f_{\text{max}} + f_{\text{min}})/2}{(f_{\text{max}} - f_{\text{min}})/2},$$

(4.7)

$$V_{DC}^{\hat{\cdot}} = \frac{V_{DC} - (V_{DC}^{\text{max}} + V_{DC}^{\text{min}})/2}{(V_{DC}^{\text{max}} - V_{DC}^{\text{min}})/2},$$

(4.8)

where $f_{\text{max}}$ and $f_{\text{min}}$ are the frequency deviation limits, and $V_{DC}^{\text{max}}$ and $V_{DC}^{\text{min}}$ are the DC bus voltage deviation limits. Subsequently, the difference between $\hat{f}$ and $V_{DC}^{\hat{\cdot}}$, $\Delta e$, is used to determine the active power converted by the ILC, as follows,

$$\Delta e = \hat{f} - V_{DC}^{\hat{\cdot}}.$$

(4.9)

$$P_{\text{ILC}} = \kappa \cdot \Delta e,$$

(4.10)

where $\kappa$ is the droop coefficient, a constant defined from the active power converter capacity. Fig. 4.3 depicts graphically the droop function governing the active power flow at the ILC.

### 4.2.4 BESS Droop Control

The use of BESSs in power systems has attracted a substantial amount of research attention due to their fast power balancing capacity, especially in microgrids with high penetration of renewable energy
sources where power generation is intermittent and difficult to predict accurately. BESSs can store energy when there is a surplus, and release it when there is a shortage, helping to maintain the power balance. In AC microgrids, BESSs are connected through bi-directional DC/AC inverters, allowing the charge and discharge of batteries. In AC islanded microgrids with multiple BESSs, their primary level controllers allow them to function with complete autonomy using only local information gathered at its coupling point. Typically, their droop functions involve system frequency and SoC versus active power injected/absorbed [34–36,38,40]. This strategy allows coordinated charging/discharging cycles, preventing circulating currents and improving the BESSs life span. In DC microgrids with multiple BESSs, their primary level droop functions typically involve DC Bus Voltage and SoC versus active power injected/absorbed [116–118]. The droop function controlling the active power dispatch of BESSs is stated as follows,

\[
f = f_{\text{nom}} - m \cdot P_{\text{BESS}}, \quad \text{in AC microgrids}
\]

\[
V_{\text{DC}} = V_{\text{nom}}^{\text{DC}} - u \cdot P_{\text{BESS}}, \quad \text{in DC microgrids}
\]

where \(m\) and \(r\) are the droop coefficient, defined as functions of their SoC in AC and DC microgrids respectively as:

\[
m = \begin{cases} 
\frac{1}{\text{SoC}} \cdot \frac{f_{\text{nom}} - f_{\text{min}}}{P_{\text{BESS, cap}}^{\text{max}} - f_{\text{nom}}}, & \text{if } f \leq f_{\text{nom}} \\
\frac{1}{1 - \text{SoC}} \cdot \frac{f_{\text{max}} - f_{\text{nom}}}{f_{\text{nom}} - P_{\text{BESS, cap}}^{\text{max}}}, & \text{if } f > f_{\text{nom}} 
\end{cases}
\]

\[
u = \begin{cases} 
\frac{1}{\text{SoC}} \cdot \frac{V_{\text{DC}}^{\text{nom}} - V_{\text{DC}}^{\text{min}}}{P_{\text{BESS, cap}}^{\text{max}} - V_{\text{DC}}^{\text{nom}}}, & \text{if } V_{\text{DC}} \leq V_{\text{DC}}^{\text{nom}} \\
\frac{1}{1 - \text{SoC}} \cdot \frac{V_{\text{DC}}^{\text{max}} - V_{\text{DC}}^{\text{nom}}}{V_{\text{DC}}^{\text{nom}} - V_{\text{DC}}^{\text{min}}}, & \text{if } V_{\text{DC}} > V_{\text{DC}}^{\text{nom}} 
\end{cases}
\]

where \(f_{\text{max}}\) and \(f_{\text{min}}\), and \(V_{\text{DC}}^{\text{max}}\) and \(V_{\text{DC}}^{\text{min}}\) are the deviation limits, SoC is the state of charge and \(P_{\text{BESS, cap}}\) is the active power injection/absorption capacities of the BESS. Fig. 4.4 depicts graphically the \(P_{\text{BESS}} - f/V_{\text{DC}} - \text{SoC}\) droop function governing the active power dispatch of the BESSs.
4.3 Consensus-Based Distributed Architecture

4.3.1 Agents

In most of the previous consensus-based distributed approaches, the Agents (capable of transmitting/receiving data and performing simple computations) are located strictly within the DGs and/or BESS controllers [76]. In this chapter, we extend the possible location of the Agents to any bus, depending on the objective being addressed. We assume that all Agents are capable of exchanging information with neighboring Agents, as long as there is a communication link between them. Agents located within DGs, BESS, or ILC are capable of resetting their droop functions, whereas Agents located at load buses are only capable of sensing and sharing their bus voltage and active power.

4.3.2 Graph Theory

The theory that describes the multi-agent system and the ratio-consensus algorithm is based on the notation established in [77] and [105]. The cyber-layer network interconnecting the agents (capable of transmitting/receiving data and performing simple computations) can be described as a directed graph \(G = (\nu, \varepsilon)\), where \(\nu = \{1, 2, ..., n\}\) is the vertex set (each vertex corresponds to an agent), and \(\varepsilon \subseteq \nu \times \nu\) is the set of edges, where \((i, j) \in \varepsilon\) if node \(i\) can receive information from node \(j\). Note that communication links may be asymmetrical, where there is a flow of information from agent \(i\) to agent \(j\), but not the converse, i.e., \((i, j) \in \varepsilon\), while \((j, i) \notin \varepsilon\). To simplify the notation, we assume self-loops for all agents, i.e., \((i, i) \in \varepsilon\), \(\forall i \in \nu\). For agent \(i\), we refer to its in-neighborhood as the set of vertexes it can receive information from, defined as \(N_i^- := \{j \in \nu : (i, j) \in \varepsilon\}\). Similarly, we refer to its out-neighborhood as the set of vertexes agent \(i\) can send information to, defined as \(N_i^+ := \{j \in \nu : (j, i) \in \varepsilon\}\). Consequently, the number of neighbors agent \(i\) can send information to is called the out-degree, and is denoted by \(D_i^+ := |N_i^+|\). Note that as a consequence of the self-loop assumption, each agent is a member of its own in- and out-neighborhood. We assume that the directed graph \(G\) is strongly connected, i.e., for each pair of agents \(i, j \in \nu\) there is a path from \(j\) to \(i\). Fig. 4.5 shows an example of a 5 agents cyber-layer.
4.3.3 Ratio-Consensus Algorithm

The ratio-consensus algorithm relies on two linear iterations executed by each agent, that eventually converge to a common value for all of them [77]. Consider that the communication network that allows the flow of information between agents can be described by the graph model detailed in the previous sub-section, i.e., graph $G = \{ v, \varepsilon \}$. Each agent $i$ maintains two internal values, named $y_i$ and $z_i$, that are updated at each iteration over time, as a weighted summation of all the internal values of its neighboring agents that can send information to agent $i$, including agent $i$ itself (given the self-loop assumption). In other words:

$$y_i[k + 1] = \sum_{j \in N^{-}_i} \frac{1}{D^+_j} y_j[k], \quad (4.15)$$

$$z_i[k + 1] = \sum_{j \in N^{-}_i} \frac{1}{D^+_j} z_j[k]. \quad (4.16)$$

After updating its internal values, and assuming that $z_i[k] > 0, \forall k$, at each iteration agent $i$ computes $\gamma_i$ as:

$$\gamma_i[k] = \frac{y_i[k]}{z_i[k]}, \quad (4.17)$$

Lemma 4.3.1 states that (4.17) converges to a common value for every agent $i$ when it tends to infinity [77].

**Lemma 4.3.1.** Let $y_i[k], \forall i$, be the result of iteration (4.15) for an initial value $y_i[0], \forall i$, and $z_i[k], \forall i$, be the result of iteration (4.16) for an initial value $z_i[0], \forall i$, with the condition of $z_i[0] > 0$; then we have that:

$$\lim_{k \to \infty} \gamma_i[k] = \frac{\sum_{j=1}^{n} y_j[0]}{\sum_{j=1}^{n} z_j[0]}, \forall i. \quad (4.18)$$

Lemma 4.3.1 implies that, through the iterative exchange of information between the distributed agents within the strongly connected directed graph $G$, each agent can obtain information not directly reachable for them. In the next sections, we extend its use to address different secondary control objectives in the hybrid AC/DC microgrid. In each particular case, a different set of information is transmitted, as well as different control actions are considered for the participating agents. The convergence speed, or the number of iterations required to reach a consensus, depends on the second largest in magnitude of the weight matrix $P = [P_{ij}]$, where $[P_{ij}] = 1/D^+_j$, when $(i, j) \in \varepsilon$, and $[P_{ij}] = 0$ otherwise [77]. Thus, the ratio-consensus algorithm guarantees that the information transmitted converges to a common value.
4.4 Objective 1: Average DC Voltage Approach for ILC Control

4.4.1 Objective Formulation

Consider a general case of a hybrid AC/DC microgrid composed of a single AC sub-grid, a single DC sub-grid, and a single bi-directional ILC, as shown in Fig. 4.2. The loading levels in both sub-grids may change over time. Both sub-grids are fed by droop-controlled DGs and interconnected at a single point by the ILC. The droop function of the ILC involves both AC sub-grid frequency and DC bus voltage deviations, as previously described in Section 4.2. Table 4.1 shows the load parameters for this and the subsequent cases, where the arrow symbols indicate changes in the loading levels at \( t = [30, 60, 90] \), respectively.

The capacity of each DG in the AC sub-grid is 10\( kW \), with nominal frequency and voltage of 50Hz and 127V\(_{AC}\), respectively. The droop coefficients for each of them are \( m = 0.0001 \) and \( n = 0.0007 \). The capacity of each DG in the DC sub-grid is 10\( kW \), with a nominal voltage of 400V\(_{DC}\). The droop coefficient for each of them is \( u = 0.002 \). The capacity of the ILC is 10\( kW \), with a droop coefficient \( \kappa = 0.0001 \). The line parameters are detailed in Table 4.2.

The capacity of each DG in the AC sub-grid is 10\( kW \), with nominal frequency and voltage of 50Hz and 127V\(_{AC}\), respectively. The droop coefficients for each of them are \( m = 0.0001 \) and \( n = 0.0007 \). The capacity of each DG in the DC sub-grid is 10\( kW \), with a nominal voltage of 400V\(_{DC}\). The droop coefficient for each of them is \( u = 0.002 \). The capacity of the ILC is 10\( kW \), with a droop coefficient \( \kappa = 0.0001 \). The line parameters are detailed in Table 4.2.

\[
V_{DC,\text{avg}} = \frac{\sum_{i=1}^{n}(V_{DC,i} - V_{\text{min}}^{DC,i})}{\sum_{i=1}^{n}(V_{\text{max}}^{DC,i} - V_{\text{min}}^{DC,i})}, \tag{4.19}
\]

Table 4.1: Load parameters

<table>
<thead>
<tr>
<th>Bus</th>
<th>P(kW)</th>
<th>Q(kVar)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8 ( \downarrow ) 2 ( \uparrow ) 7.3 ( \downarrow ) 1.3</td>
<td>1.5 ( \downarrow ) 0.6 ( \uparrow ) 1.4 ( \downarrow ) 0.7</td>
</tr>
<tr>
<td>3</td>
<td>7 ( \downarrow ) 1 ( \uparrow ) 6.3 ( \downarrow ) 0.3</td>
<td>1 ( \downarrow ) 0.1 ( \uparrow ) 0.9 ( \downarrow ) 0.2</td>
</tr>
<tr>
<td>7</td>
<td>4.5 ( \downarrow ) 0.5 ( \uparrow ) 8.5 ( \downarrow ) 4.5</td>
<td>–</td>
</tr>
<tr>
<td>9</td>
<td>5.5 ( \downarrow ) 1.5 ( \uparrow ) 9.5 ( \downarrow ) 5.5</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 4.2: Line parameters

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>R(( \Omega ))</th>
<th>X(( \text{mH} ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>0.020</td>
<td>0.127</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>0.080</td>
<td>0.509</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0.060</td>
<td>0.381</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>0.040</td>
<td>0.254</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>0.010</td>
<td>0.063</td>
</tr>
<tr>
<td>7</td>
<td>8</td>
<td>0.100</td>
<td>–</td>
</tr>
<tr>
<td>7</td>
<td>10</td>
<td>0.050</td>
<td>–</td>
</tr>
<tr>
<td>8</td>
<td>9</td>
<td>0.200</td>
<td>–</td>
</tr>
<tr>
<td>8</td>
<td>11</td>
<td>0.020</td>
<td>–</td>
</tr>
<tr>
<td>9</td>
<td>12</td>
<td>0.050</td>
<td>–</td>
</tr>
</tbody>
</table>

Although the power balance is guaranteed by the primary level controllers, the ILC droop function may not reflect accurately the loading levels of the sub-grids, due to DC bus voltage deviations. Therefore, we propose the use of an average DC bus voltage variable to obtain a more accurate representation of the loading level of the DC sub-grid, and consequently to improve the power flow between sub-grids. The average DC bus voltage variable was previously proposed and used in [115], to control the charge/discharge rates of BESSs in a DC microgrid, and is defined as follows,
where $V_{DC,i}$ is the DC bus voltage measured by the participating agent $i$. The proposed normalized values for constructing the droop function for the ILC are defined as follows,

$$
\hat{f} = \frac{f - (f_{i}^{max} + f_{i}^{min})/2}{(f_{i}^{max} - f_{i}^{min})/2}, \tag{4.20}
$$

$$
V_{DC,avg} = \frac{V_{DC,avg} - (V_{DC,avg}^{max} + V_{DC,avg}^{min})/2}{(V_{DC,avg}^{max} - V_{DC,avg}^{min})/2}, \tag{4.21}
$$

where $f_{i}^{max}$ and $f_{i}^{min}$ are the frequency deviation limits, and $V_{DC,avg}^{max}$ and $V_{DC,avg}^{min}$ are the DC sub-grid bus voltage deviation limits. Posteriorly, the difference between $\hat{f}$ and $V_{DC,avg}$, $\Delta e^*$, is used to determine the active power converted by the ILC, as follows,

$$
\Delta e^* = \hat{f} - V_{DC,avg}, \tag{4.22}
$$

$$
P_{ILC}^* = \kappa \cdot \Delta e^*, \tag{4.23}
$$

where $\kappa$ is the droop coefficient, defined from the active power converter capacity. Therefore, to obtain the average DC bus voltage variable, the consensus distributed algorithm is implemented.

### 4.4.2 Consensus Algorithm

![Physical and cyber-topologies of the hybrid AC/DC microgrid for addressing the objective 1.](image)

**Figure 4.6:** Physical and cyber-topologies of the hybrid AC/DC microgrid for addressing the objective 1.

As stated before, the consensus protocol guarantees that the information transmitted converges to a common value. To address this objective, and assuming that realizing consensus of all buses within the DC sub-grid is not possible [115], the agents are located preferable (but not necessarily) within the ILC and DGs in the DC sub-grid. The data transmitted by the agents are DC bus voltages and
4.4. OBJECTIVE 1: AVERAGE DC VOLTAGE APPROACH FOR ILC CONTROL

their deviation limits. The physical and cyber-topologies of the hybrid AC/DC microgrid are shown in Fig. 4.6. The internal values $y_i[0]$ and $z_i[0]$ are initialized as follows,

$$y_i[0] = V_{DC,i} - V_{DC,i}^{min},$$
\hspace{1cm} (4.24)

$$z_i[0] = V_{DC,i}^{max} - V_{DC,i}^{min}.$$  
\hspace{1cm} (4.25)

Lemma 4.3.1 implies that agent $i$ can eventually obtain $\gamma_i[k]$, which in this case is the average DC voltage proportional to the average DC voltage deviations, as defined in (4.19). Posteriorly, after a consensus is reached, the ILC controller adjusts its converted active power according to its droop function, as detailed from (4.20)-(4.23).

4.4.3 Simulation Results

Fig. 4.7 shows the performance of the approach. The consensus time-span is 3 minutes. Every time a consensus is reached, the average DC voltage variable is obtained, and used by the ILC in its droop function power dispatch.
4.5 Objective 2: Proportional Active Power Sharing

4.5.1 Objective Formulation

Proportional active power dispatch in traditional AC islanded microgrids can be successfully achieved by the primary level droop controllers, since the droop functions directly involve active power vs system frequency. But in the case of DC islanded microgrids, where the primary level droop functions involve active power vs DC bus voltage, the line resistors may cause bus voltage deviations, leading to a dis-proportional active power dispatch [108,115]. Therefore, we propose a distributed consensus algorithm for hybrid AC/DC islanded microgrid to address this classic objective [77]. The proportional active power dispatch for each participating DG $i$ is defined as:

$$P_i^* = \frac{\sum_{j=1}^{n}(P_j - P_{jmin})}{\sum_{j=1}^{n}(P_{jcap} - P_{jmin})},$$

(4.26)

where $P_i^*$ is the objective active power dispatch of DG $i$, as a proportion of the total active power dispatch being generated and the total active power capacity. $P_{jmin}$ refers to the lower generation boundary of a DG (a minimum power generation a DG may have). Thus, in order to obtain $P_i^*$ for each DG, the consensus algorithm is implemented.

4.5.2 Consensus Algorithm

The consensus algorithm is implemented as a secondary level control for DGs, in order to proportionally share the total active power dispatch. To reach a consensus, each DG is assumed to be an agent. The data transmitted by the agents are active power dispatch and active power generation.

Figure 4.8: Physical and cyber topologies of the hybrid AC/DC microgrid for achieving proportional active power dispatch.

The consensus algorithm is implemented as a secondary level control for DGs, in order to proportionally share the total active power dispatch. To reach a consensus, each DG is assumed to be an agent. The data transmitted by the agents are active power dispatch and active power generation.
limits. Fig. 4.8 depicts both the physical and cyber layers of the hybrid AC/DC microgrid in this case scenario. For each DG \( i \), the internal values \( y_i[0] \) and \( z_i[0] \) are initialized as follows,

\[
y_i[0] = P_i - P^\text{min}_i, \quad (4.27)
\]
\[
z_i[0] = P^\text{cap}_i - P^\text{min}_i. \quad (4.28)
\]

Lemma 4.3.1 implies that agent \( i \) can eventually obtain \( \gamma_i[k] \), which in this case is the average active power dispatch, proportional to the total active power generation capacity of the system, as defined in (4.26). Posteriorly, after a consensus is reached, each DG knows the proportion of its active power capacity that must generate. Subsequently, each DG \( i \) can reset their droop function to a new \( f_{i}^{\text{nom}} \) or \( V_{DC,i}^{\text{nom}} \) that supplies active power \( P_i^* \), as follows,

\[
f_{i}^{\text{nom}} = f - m_i \cdot P_i^*, \quad \text{if AC-side DG}, \quad (4.29)
\]
\[
V_{DC,i}^{\text{nom}} = V_{DC,i} - u_i \cdot P_i^*, \quad \text{if DC-side DG}, \quad (4.30)
\]

where \( P_i^* \) is the proportional active power dispatch, as in (4.26).

### 4.5.3 Simulation Results

Figs. 4.9 shows the performance of the algorithm. The consensus time-span is 3 minutes. Every time a consensus is reached, the set-points of the droop functions are updated and the total required active power is proportionally shared by the DGs. Consequently, the ILC converts the active power necessary to maintain the balance.

### 4.6 Objective 3: AC Frequency and Average DC Voltage Restoration

#### 4.6.1 Objective Formulation

AC frequency restoration in AC microgrids is a classic secondary objective. In the particular case of hybrid AC/DC microgrids, this objective is still valid and accounts for restoring the system frequency of the AC sub-grid. Regarding the DC sub-grid, the homologous objective is the DC bus voltage restoration. However, considering a general case where differences in line resistors exist and cause voltage deviations in all buses, restoration of the DC average bus voltage is a suitable objective. The use of the DC average bus voltage for governing the ILC power flow was previously introduced and addressed in Section 4.4, and it can be used and extended in this case. Therefore, if the droop controller of the ILC involves both AC sub-grid frequency and average DC bus voltage deviations, and if both values are restored and brought close to zero, as a result, the active power converted by the ILC is brought to zero as well. This objective is valid and of particular interest in cases where both grids are interconnected only to provide temporary support, e.g. in case of a sudden change of loading level in one of them.
4.6.2 Consensus Algorithm

In this case, agents are located within the DGs in both sides of the hybrid AC/DC microgrid, including the ILC. Each agent in the AC sub-grid transmits its frequency reading and its deviation limits. On the other hand, each agent in the DC sub-grid transmits its DC bus voltage and its deviation limits. Since both sub-grids share a different set of data, two cyber layers are considered in this scenario, with the ILC agent participating in both of them, as shown in Fig. 4.10. For each DG $i$ in the DC sub-grid, the internal values are initialized as follows,

$$y_{DC,i}[0] = V_{DC,i} - V_{DC,i}^{min},$$

$$z_{DC,i}[0] = V_{DC,i}^{max} - V_{DC,i}^{min},$$

while for each DG $i$ in the AC sub-grid, the internal values are initialized as follows,

$$l_{y_{AC,i}}[0] = f_i - f_i^{min},$$

$$z_{AC,i}[0] = f_i^{max} - f_i^{min}.$$ 

Lemma 4.3.1 implies that agent $i$ can eventually obtain $\gamma_i[k]$, which for the DC sub-grid is the average DC voltage, and for the AC sub-grid is the average AC frequency, being both proportional to their deviation limits. Therefore, after a consensus is reached, the ILC controller adjusts its converted active power according to its droop function, as previously detailed in section 4.4. Also, agents within DGs
reset their droop functions to restore AC frequency and average DC voltage, in both AC and DC sub-grids, respectively as follows,

\[ f_{i}^{\text{nom}} = f_{i}^{\text{nom}} + (50 - f_{\text{avg}}), \text{ if AC-side DG}, \]

\[ V_{DC,i}^{\text{nom}} = V_{DC,i}^{\text{nom}} + (400 - V_{DC,avg}), \text{ if DC-side DG}, \]

where \( f_{\text{avg}} \) and \( V_{DC,avg} \) are the average values obtained through the consensus algorithm.

4.6.3 Simulation results

Fig. 4.11 shows the performance of the strategy. The consensus time-span is 3 minutes. Every time a consensus is reached, the set-points of the droop functions are updated and the AC frequency and average DC bus voltage are restored. In consequence, the power converted by the ILC drops to zero.

4.7 Objective 4: BESSs Coordination

4.7.1 Objective Formulation

In the particular case of the hybrid AC/DC microgrids, BESSs can be located on either sub-grid, inheriting both primary level control strategies and their respective drawbacks. Since their droop-based control strategies are different and involve either AC or DC local readings, proper coordination for charge and discharge cycles is not directly possible at a primary level. For this matter, we propose the use of a distributed secondary control based on a consensus algorithm to coordinate the active power injection/absorption of AC and DC BESSs, while maintaining the primary level quick response to load
Figure 4.11: AC frequency and average DC voltage restoration: simulation results.
fluctuations, using a dispatch function composed as follows,

\[ P_{BESS} = f(\text{Microgrid total loading, SoC, local measurements, instant power capacity}) , \]

where the microgrid total loading component is acquired through consensus, the SoC is an inner state and the local measurements are AC frequency and DC bus voltage, sensed at the coupling point. Hence, consider a hybrid AC/DC microgrid, composed of a single AC sub-grid, a single DC sub-grid, and a single bi-directional ILC.

4.7.2 Consensus Algorithm

Consider the system topology previously presented, with BESSs located in both sides of the microgrid, as shown in Fig. 4.12. The converter capacity of BESS in the AC sub-grid (bus 5) is 10 kW, with nominal frequency and voltage of 50 Hz and 127 VAC, respectively. The converter capacity of each BESS in the DC sub-grid (buses 10 and 12) is 10 kW, with a nominal voltage of 400 VDC. To construct the active power injection/absorbing function, each BESS and DGs within the hybrid AC/DC microgrid is assumed to be an agent. Since all DGs participate in the consensus, the proportional active power share objective can be addressed at the same time. Agents transmit their active power generation/absorption and their capacity limits. The objective for the BESSs is to coordinate their charging/discharging cycles, proportional to the microgrid total loading level, their SoC and active power capacities. The objective for the DGs is to achieve proportional active power dispatch. Thus, for each agent \( i \), the internal values are initialized as follows,

\[ y_i[0] = P_i - P_i^{min}, \quad (4.37) \]

Figure 4.12: Physical and cyber topologies of the hybrid AC/DC microgrid for achieving BESSs coordination.
Lemma 4.3.1 implies that agent \( i \) can eventually obtain \( \gamma_i[k] \), which, for DGs, is the corresponding active power dispatch, proportional to its active power generation capacity. For BESSs, \( \gamma_i[k] \) represents the total loading level of the microgrid system as a proportion of the entire generation capacity. Consequently, after a consensus is reached, BESSs can coordinate its active power injection/absorption as a function of the total loading level of the system and its SoC, proposed in this study as a simple tuned association of both secondary level consensus algorithm and a primary level droop function, as shown in Fig. 4.13, and defined as:

\[
P_i = P_{i,sec} + P_{i,prim},
\]

where \( P_{i,sec} \) is the tuned contribution part of the secondary level consensus algorithm, while \( P_{i,prim} \) is the corresponding part of the droop control with quick response to load fluctuations. Both are defined as follows,

\[
P_{i,sec} = \begin{cases} 
\alpha \cdot \gamma^* \cdot \text{SoC}_i \cdot P_{\text{cap},i}, & \text{if } \gamma^* \geq 0, \\
\alpha \cdot \gamma^* \cdot (1 - \text{SoC}_i) \cdot P_{\text{cap},i}, & \text{if } \gamma^* < 0,
\end{cases}
\]

\[
P_{i,prim} = \begin{cases} 
\frac{f_{\text{nom}} - f}{m_i^*}, & \text{if AC-side BESS}, \\
\frac{V_{\text{DC},i}^\text{nom} - V_{\text{DC},i}}{u_i^*}, & \text{if DC-side BESS},
\end{cases}
\]

where \( \gamma^* \) is the total loading level of the microgrid system obtained by the consensus algorithm, and normalized to a value between \([-1, 1]\), so that, a negative value of \( \gamma^* \) means that the system is at less than a half of its total generation capacity, and \( m_i^* \ u_i^* \) are the droop coefficients dynamically computed as functions of the SoC, for BESSs in the AC and DC sides respectively as follows,

\[
m_i^* = \begin{cases} 
\frac{1}{\text{SoC}_i} \cdot \frac{f_{\text{nom}} - f_{\text{min}}}{P_{\text{cap},i} \cdot \beta}, & \text{if } f \leq f_{\text{nom}} \\
\frac{1}{1 - \text{SoC}_i} \cdot \frac{f_{\text{max}} - f_{\text{nom}}}{P_{\text{cap},i} \cdot \beta}, & \text{if } f > f_{\text{nom}},
\end{cases}
\]
4.7. OBJECTIVE 4: BESSS COORDINATION

Figure 4.14: BESSs coordination: simulation results.

\[
u_i^* = \begin{cases} 
\frac{1}{1 - \text{SoC}_i} \cdot \frac{V_{\text{nom}}_{DC,i} - V_{\text{min}}_{DC,i}}{V_{\text{cap},i}^{P_{\text{cap},i}} - V_{\text{nom}}_{DC,i}}, & \text{if } V_{DC,i} \leq V_{\text{nom}}_{DC,i}, \\
\frac{1}{1 - \text{SoC}_i} \cdot \frac{V_{\text{nom}}_{DC,i} - V_{\text{min}}_{DC,i}}{V_{\text{nom}}_{DC,i} - V_{\text{cap},i}^{P_{\text{cap},i}}}, & \text{if } V_{DC,i} > V_{\text{nom}}_{DC,i}, 
\end{cases}
\]

(4.43)

where \( \alpha \) and \( \beta \) are the weight variables for tuning the respective contribution of \( P_{i,sec} \) and \( P_{i,prim} \), with the condition of \( \alpha + \beta = 1 \), in order to maintain the power dispatch within the capacity limits. Also, each DG \( i \) resets their droop function to a new \( f_{i}^{\text{nom}} \) or \( V_{\text{nom}}_{DC,i} \) that supplies the corresponding active power \( P_i^* \), as follows,

\[
f_{i}^{\text{nom}} = f - m_i \cdot P_i^*, \quad \text{if AC-side DG},
\]

(4.44)

\[
V_{\text{nom}}_{DC,i} = V_{DC,i} - u_i \cdot P_i^*, \quad \text{if DC-side DG}.
\]

(4.45)

4.7.3 Simulation results

Fig. 4.14 shows the performance of the strategy. The consensus time-span is 3 minutes. For this case, \( \alpha = 0.8 \) and \( \beta = 0.2 \). Every time a consensus is reached, the set-points of the dispatch functions of DGs and BESSs are updated. The power injected/absorbed by the BESSs is coordinated, bringing the SoCs to eventually converge. The power generated by the DGs is proportionally shared.
4.8 Interim Conclusion

In this chapter, we have proposed a distributed control architecture for hybrid AC/DC islanded microgrids, to address some of the most common secondary level objectives, such as proportional active power sharing, DC average voltage for improving the ILC power flow, AC frequency and DC average voltage restoration, and BESSs coordination. The distributed architecture is implemented using a low-bandwidth neighbor-to-neighbor communication network known as a multi-agent system. Agents are located at different buses within the hybrid microgrid, depending on the particular objective being addressed, gathering local information and sharing it with other neighboring agents. For this study, we have considered the most general case of a hybrid AC/DC islanded microgrid, with no dominant sub-grid. Extensive simulation results verify the effectiveness of the proposed approach. Future work includes dynamic and stability analysis.
Chapter 5

Optimization of Reconfigurable Islanded Microgrids using Random Forest Classifier

ABSTRACT

In this chapter, a random forest classifier is developed as an approach to find the optimal configuration of islanded microgrids. In islanded microgrids with high penetration of renewable sources, the power generation may be intermittent and unpredictable. Moreover, even when forecast information is available, the non-dispatchable nature of these generation units further limits the control variables needed to formulate and address an optimization problem. In this regard, reconfigurable microgrids allow controlled changes in the grid topology to redirect and redistribute the power flow, in order to optimize and/or improve the system resiliency. In these scenarios, the optimization variables are the binary status (closed/open) of the controllable switches, which make the problem particularly suitable to be addressed by decision classification trees. In this study, the optimization objective is power loss minimization, subject to the system constraints of power flow and supply/demand balance. Initially, a decision tree classifier is introduced, and tested on a simple 9-Bus islanded system to identify and categorize different generation and loading level profiles of the system, and learn from them the optimal configurations. After that, a random forest classifier is designed as an ensemble of decision trees with enhanced capabilities. A time series learning component is also implemented to boost the time-related learning characteristics of the classifier, such as trend and seasonality, which are inherent to the power generation levels of renewable energy sources. The proposed random forest classifier is tested on the modified IEEE 33-Bus islanded microgrid test system. Simulation results show the random forest classifier, when sufficiently trained, is able to find the optimal configuration of the microgrid to any new generation and loading profile.

The content of this chapter is mainly based on and modified from the following paper prepared for submission:
CHAPTER 5. OPTIMIZATION OF RECONFIGURABLE ISLANDED MICROGRIDS USING RANDOM FOREST CLASSIFIER


5.1 Introduction

In the past few decades, the concept of microgrid has gained special attention from researchers and engineers, due to its versatility to include different distributed energy resources and power devices. However, the relatively small scale of the DGs and the intermittency and unpredictability of the RESs brings new control challenges not previously seen in traditional power systems [3]. Particularly, in the case of islanded microgrids, the disconnection from a main grid, and the uncertainty of the power generation of energy sources that rely on weather conditions, heavily compromises the power balance of the system. Therefore, taking into account the limitations of the DGs in these scenarios, minimizing the power loss in the transmission lines becomes an important problem to address in order to maintain the supply/demand balance of islanded microgrids.

The non-dispatchable nature of the RESs limits the control variables needed to formulate an optimization problem, as they typically work under a MPPT control technique. However, reconfigurable microgrids allow controlled changes in the grid topology to redirect and redistribute the power flow, using control switches distributed along the system. Such particularity grants the EMS with binary (closed/open) control variables that can be used to formulate an optimization problem, even in scenarios where the system is mainly composed by non-dispatchable DGs. Optimization approaches for reconfigurable microgrids have been developed previously, and can be extensively found in literature. A review of approaches is presented in [64], where a classification of objectives, algorithms, and constraints is highlighted. In [65], the minimization of fuel consumption problem is addressed using a non-dominated sorting genetic algorithm II. In [66], a genetic algorithm is used to maximize the loads supplied by the system. In [119], a vulnerability system index is introduced, and maximized using an artificial physics optimization algorithm with a searching vector. The restoration after natural disasters can be addressed as a reconfiguration problem, as presented in [120] and solved using a multi-agent distributed approach. In [121], the restoration problem is addressed using a semidefinite programming approach. Although all the previously cited papers formulate and solve their respective optimization problems, most of the approaches are based on linear programming or evolutionary algorithms (e. g. genetic algorithms, particle swarm optimization algorithms) that need to reformulate the problem for every input received [122]. Regarding machine learning-based approaches, a study using gated recurrent units (GRUs) to optimize the operational cost of reconfigurable microgrids was presented in [123]. However, since the approach we are presenting in this chapter differs from all previously presented optimization techniques, especially regarding the optimization objective and microgrid composition, a direct comparison is impossible to make.

In this work, a decision tree and a random forest learner are trained to find the optimal configuration of islanded microgrids integrated mainly with non-dispatchable DGs. A decision tree classifier is a versatile machine learning algorithm that can be used for regression and classification tasks. For
classification, the decision tree model is trained on a dataset of input feature values and their corresponding output class labels. During training the model builds a decision tree composed of nodes and edges, where a node represents a decision based on one of the feature values and the edges lead to another node based on the outcome of the decision (see Figure 5.5 as an example). The tree can then be used to predict the resulting class for unseen input values. Their low level of abstraction makes them easy to build, train, tune, and evaluate. They have extensive applications due to the simplicity of the models and the fact that the resulting model is human-interpretable and computationally inexpensive to evaluate. Random forest classifiers are ensembles of decision trees that can enhance the overall performance of the prediction model (see [124]). Regarding their applications in microgrids, an approach to identify islanding incidents by systematically classifying a structure of system features from local bus voltages, line currents, and system events, is presented in [125]. Also, an energy storage system planning and energy balancing methodology for planned communities is proposed in [126], where decision trees are used as an scheduling tool to maintain the power balance within the system. In this study, two different microgrid test systems are investigated, a simple 9-Bus system and a modified IEEE 33-Bus islanded microgrid test system, both including switches to reconfigure the topology of the microgrids depending on the power demand and RESs generation [127]. For both systems, off-line data of loading/generation power profiles are generated and tested on all feasible grid configurations. The best scenarios are then revised and stored. These are consequently used as class labels to train the learning model. Also, in order to integrate the seasonal characteristics of the power profiles, a time series learning component is included in the input data. A decision tree classifier and a random forest model are then trained on the developed training set to find an optimized configuration of the switches for the two test cases respectively. Once the models are trained, their performance is tested on a hold-out test set. Both models prove to be capable of successfully classifying any test set input and select one of the pre-determined classes which represent feasible topology configurations, without violating any operational constraint.

The main contributions of this work are highlighted as follows:

1. A first approach training decision tree and random forest classifiers to tackle an optimization problem in reconfigurable islanded microgrids with reduced and limited dispatch capabilities is demonstrated.

2. Once on-line, for any determined loading and power generation profile, a feasible and optimized microgrid configuration can be found in real time following the rules determined by the decision tree and random forest classifier.

3. The computation requirements of the deployment are minimal, since the heavy computation is done at the training stage.

The remainder of this chapter is organized as follows. In Section 5.2 the formulation of the reconfigurable islanded microgrid is presented, as well as a brief description of the system constraints. In Section 5.3 the proposed decision tree and random forest classifier models are described in detail. Section 5.4 presents the simulation results. A conclusion is drawn in Section 5.5.
5.2 Reconfigurable Islanded Microgrid Formulation

5.2.1 Microgrid Power Balance

The islanded microgrids in this study have high penetration of renewable energy sources. Without lose of generality, we assume the DGs within the system rely on weather conditions and have MPPT primary level controllers that maximize their output power. Since these DGs are non-dispatchable, the inclusion of at least one dispatchable DG is required, in order to compensate for the supply/demand fluctuations and to maintain the power balance. These dispatchable DGs can be either diesel generators, fuel cells, or any generation unit with droop-based primary controllers. The system and the power balance formulation are described next.

The set of buses is defined as \( N = \{1, 2, \ldots, n\} \), the set of renewable energy DGs is represented as \( A = \{1, 2, \ldots, a\} \), the set of dispatchable DGs is defined as \( B = \{1, 2, \ldots, b\} \), \( C = \{1, 2, \ldots, c\} \) is the set of loads, and \( E = \{1, 2, \ldots, e\} \) represents the set of lines in the microgrid. Therefore, the power balance of the system can be formulated as follows,

\[
\sum_{i \in A} P_{\text{res},i} + \sum_{j \in B} P_{\text{disp},j} = \sum_{k \in C} P_{\text{load},k} + \sum_{l \in E} P_{\text{line},l},
\]

(5.1)

where \( P_{\text{res},i} \) is the active power supplied by the renewable energy source \( i \); \( P_{\text{disp},j} \) is the active power supplied by the dispatchable DG \( j \); \( P_{\text{load},k} \) is the active power dragged by the load \( k \); and \( P_{\text{line},l} \) is the power dissipated by the transmission line \( l \).
5.2. RECONFIGURABLE ISLANDED MICROGRID FORMULATION

We assume that the total RESs power generation capacity is intentionally dimensioned to be below the total power demand, and no curtailment actions are required, by satisfying the following restriction:

\[ \sum_{i \in A} P_{\text{res},i} \leq \sum_{k \in C} P_{\text{load},k}. \]  \hspace{1cm} (5.2)

Finally, we assume that the dispatchable DGs have droop-based controllers that satisfy the supply/demand at any time, as long as their output power does not exceed their power capacities. Without lose of generality, their droop functions are described as follows,

\[ f = f^*_j - m_{p,j} \cdot P_{\text{disp},j}, \quad j \in B \]  \hspace{1cm} (5.3)

\[ |V_j| = V^*_j - n_{q,j} \cdot Q_{\text{disp},j}, \quad j \in B \]  \hspace{1cm} (5.4)

where \( f^*_j \) and \( V^*_j \) are the nominal system frequency and bus voltage, \( P_{\text{disp},j} \) and \( Q_{\text{disp},j} \) are the active and reactive powers supplied by the DG \( j \), and \( m_{p,j} \) and \( n_{q,j} \) are the droop coefficients, computed from:

\[ m_{p,j} = \frac{f^*_j - f_{\text{min}}}{P_{\text{cap}}_{\text{disp},j}}, \quad j \in B \]  \hspace{1cm} (5.5)

\[ n_{q,j} = \frac{V^*_j - V_{\text{min}}}{Q_{\text{cap}}_{\text{disp},j}}, \quad j \in B \]  \hspace{1cm} (5.6)

where \( P_{\text{cap}}_{\text{disp},j} \) and \( Q_{\text{cap}}_{\text{disp},j} \) are the DG power capacities. It is worth mentioning that analyses on the dimensioning and sizing of the entire system are beyond the scope of this study.

5.2.2 Objective and System Constraints

The objective is to minimize the power loss of the system, which is the total power dissipated by the entire set of transmission lines, defined as follows:

\[ \min \sum_{l \in E} P_{\text{loss},l}, \]  \hspace{1cm} (5.7)

with solutions subject to system constraints of power generation capacities, and bus voltages and branch currents limits, as determined as follows:

\[ V^\text{min}_n \leq V_n \leq V^\text{max}_n, \quad n \in N, \]  \hspace{1cm} (5.8)

\[ I_l \leq I^\text{max}_l, \quad l \in D, \]  \hspace{1cm} (5.9)

\[ P_{\text{res},i} \leq P_{\text{cap}}_{\text{res},i}, \quad i \in A, \]  \hspace{1cm} (5.10)

\[ P_{\text{disp},j} \leq P_{\text{cap}}_{\text{disp},j}, \quad j \in B. \]  \hspace{1cm} (5.11)

System radiality is a hard constraint [128,129], enforced by considering only radial topology configurations as feasible solutions. Without loss of generality, the RCSs are limited to one action per hour,
in order to prevent an excess of disturbances in the grid caused by opening and closing power switches.

5.3 Decision Tree and Random Forest

Let $S = [s_{l_1}, s_{l_2}, ..., s_{l_e}]$ define the set of switches in the system, where $l_i$ in this case represents a line that contains a switch. The set $R \subset \mathcal{P}(S)$ denotes the set of radial closed switch configurations, which is a subset of the power set of switches. These configurations represent the possible class labels for the classifier models. A configuration $\tilde{r} \in R$ therefore represents a set of switches that are currently closed. For the sake of simplicity we numerate the different radial configuration $R = [1, 2, ..., r]$, so that $R$ contains $r$ switch configurations. The discrete set of time within a day is defined as $T = [1, 2, ..., 24]$, while the set of days within a year is defined as $D = [1, 2, ..., 365]$. The set of active power dragged and generated by the $n$-bus system at a day $d$ and a time $t$ is represented as $F_{d,t} = [P_{1,d,t}, P_{2,d,t}, ..., P_{n,d,t}]$, and is referred to as a power profile. The optimal configuration of closed switches for a particular power profile $F_{d,t}$, at a day $d$ and a time $t$ is defined as $G(F_{d,t}) = \hat{r} \in R$.

Figure 5.2: General structure of the classification system.

![Figure 5.2: General structure of the classification system.](image)

Figure 5.3: Power profiles affected by weather seasons.

The general structure for using a classification model, such as a decision tree or random forest learner,
is shown in Figure 5.2. Decision trees are not naturally suitable to classify time series data. However, with the inclusion of historical information as input features, the time series information can be included in the learning process, as seen in [130–132]. This is described in more detail in the following sub-section.

5.3.1 Training Stage

The yearly periodic effects of weather seasons on the power generation levels of RESs is known as seasonality, and it is considered in the training profiles in this study, as shown in Fig. 5.3.

To generate the training dataset, an extensive series of power profiles $F_{d,t} = [P_{1,d,t}, P_{2,d,t}, \ldots P_{n,d,t}]$ are sequentially generated using typical time-consistent RESs power generation and load functions, with considerations of seasonality trends [133, 134]. For each time step, the optimal radial configuration is found by solving the power flow for each feasible radial configuration of the grid, and saving the one with the lowest power loss. During the power loss calculations hard constraints of power limits are taken into account, and the radiality constraint is enforced by only allowing radial network configurations as class labels. In addition to the power profile features $F_{d,t}$ for each day and time, information of the hour, the day, as well as the class output for the previous hours and day are included as features. The labeled data is then used for training the classifier model, as shown in Fig. 5.4, where the inclusion of information of previous days and hours is pointed out. How important the inclusion of historical data can be for the predicted class depends on the consistency of the trends contained and captured in the training dataset.

The creation of the training dataset can be briefly summarized as follows,

Steps 1 to 4 are executed sequentially for a predefined number of days.

- Step 1. For a day $d$ and a time $t$, generate a power profile $F_{d,t} = [P_{1,d,t}, P_{2,d,t}, \ldots P_{n,d,t}]$ that includes all loads and RESs in the system.
Steps 2 and 3 are executed for all possible radial configurations \( \tilde{r} \in R \) in a loop.

- Step 2. Solve the islanded AC microgrid power flow for \( F_{d,t} \) on configuration \( \tilde{r} \).

- Step 3. Evaluate the power flow results with constraints 5.8 to 5.11.

- Step 4. Obtain the configuration \( \tilde{r} \) with the lowest power loss, and label the power profile as \( \text{class} = \tilde{r} \), along with the information of day \( d \) and time \( t \).

Once the training dataset is obtained and labeled, it is used to build the decision tree and the random forest.

![Decision tree example](image)

**Figure 5.5:** Decision tree example.

A decision tree is composed of a set of nodes and edges, representing decisions based on the feature input values. Starting at the root node, the decision tree is traversed until one reaches a leaf node that predicts the resulting class. An example is shown in Figure 5.5.

Using the training dataset, the tree is grown using measurements of impurity to quantify the quality of a split in a node [135]. The decision tree model for this study was built using the Scikit-Learn decision tree classifier, which makes use of the CART training algorithm as described in [136, 137]. This algorithm builds a binary decision tree. Searching for the feature \( f \) and threshold value \( t_f \) that leads the lowest impurity measurements in the child nodes, the dataset is recursively split into two parts until either the maximum depth of the tree is reached or until the impurity value can no longer be reduced. The impurity measurement used for this study is the gini impurity, which is an attribute of each node in the decision tree. The gini score for the \( i^{th} \) decision node is calculated as follows [136]:

\[
G_i = 1 - \sum_{k=1}^{c} p_{i,k}^2,
\]  

\[ (5.12) \]
where the index $k$ iterates through all classes $1, \ldots, c$ and $p_{i,k}$ describes ratio of instances in class $k$ at this node. A gini score of 0 therefore means that the node is "pure" because all instances belong to the same class. The cost function that is used in the CART algorithm for each feature and threshold pair $(f, t_f)$ is

$$J(f, t_f) = w_{\text{left}} \cdot G_{\text{left}} + w_{\text{right}} \cdot G_{\text{right}}, \quad (5.13)$$

where $w_{\text{left/right}}$ is the fraction of instances in the left/right child node over all instances in the two child nodes and $G_{\text{left/right}}$ is the gini score of the left/right child node (see [136]). A random forest classifier is an ensemble of decision trees that in general outperforms a single one by training multiple divers decision trees simultaneously [124, 136]. Each tree is trained on a bootstrapped sample of the training set. Additionally, a random subset of features is used for each split node to increase the diversity in the ensemble.

### 5.3.2 Using the Classifier for Microgrid Reconfiguration

Once the set of decision rules obtained in the training stage is used to categorize a classification dataset. For each power profile $F_{d,t} = [P_{1,d,t}, P_{2,d,t}, \ldots P_{n,d,t}]$, a solution $G(F_{d,t}) = \hat{r} \in [1, 2, \ldots, r]$ is found. It is posteriorly evaluated in the islanded AC microgrid model, and the performance is evaluated. The classification results can be portrayed in a confusion matrix, displaying all positive and negative predictions for each class. Finally, the accuracy of the classifiers can be simply calculated with the following equation:

$$\text{Classifier Accuracy} = \frac{\text{Correctly classified instances}}{\text{Total number of instances}}. \quad (5.14)$$

### 5.4 Simulation Results

In order to test the feasibility of the proposed optimization classifier, an islanded AC microgrid model developed in MATLAB coding environment is presented. Two test cases are included.

#### 5.4.1 9-Bus Test Case

**Table 5.1**: Line parameters of 9-Bus test system

<table>
<thead>
<tr>
<th>Line</th>
<th>R(Ω)</th>
<th>X(mH)</th>
<th>Line</th>
<th>R(Ω)</th>
<th>X(mH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.077</td>
<td>0.015</td>
<td>5</td>
<td>0.084</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>0.231</td>
<td>0.040</td>
<td>6</td>
<td>0.133</td>
<td>0.04</td>
</tr>
<tr>
<td>3</td>
<td>0.217</td>
<td>0.070</td>
<td>7</td>
<td>0.119</td>
<td>0.035</td>
</tr>
<tr>
<td>4</td>
<td>0.245</td>
<td>0.045</td>
<td>L1</td>
<td>0.147</td>
<td>0.04</td>
</tr>
<tr>
<td>L2</td>
<td>0.154</td>
<td>0.045</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A simple 9-Bus test system is used to demonstrate the effects of the power generation levels of RESs on the system optimal configuration. Figure 5.6 shows the topology of the microgrid in this case study, while Table 5.1 contains the line parameters. In this simulation, DG1 is chosen to be a droop-controlled dispatchable unit (such as a diesel generator), while DG2 is a non-dispatchable RES (more
specifically, a photo-voltaic system). Since this a relatively simple microgrid system, only two feasible radial configurations are possible: one being a closed switch in L1 and an open switch in L2, and vice-versa.

To train the classifier, an extensive series of power profiles \( F_{d,t} = [P_{1,d,t}, P_{2,d,t}, \ldots P_{n,d,t}] \) are sequentially generated using a typical photo-voltaic generation profile, covering 26,280 input power profiles covering each hour of overall 1094 days. The loading profiles are assumed to be commercial [134]. After the training stage is completed, the decision tree is built, as seen in Figure 5.7. We can see that the split that greater reduces the entropy of the dataset in first instance is the one of Bus 6, which in this case is the photo-voltaic system. Using 10-fold cross validation, which means dividing the dataset...
5.4. SIMULATION RESULTS

![Confusion Matrix](image)

**Figure 5.8:** Resulting confusion matrix of the 9-Bus test system after evaluation.

...into ten disjoint subsets, and training a decision tree on nine of the subsets while evaluating the tree on the left-out subset, has resulted in an average accuracy of 99.94% with a standard deviation of 0.03 and an average F1-score of 0.9993. The F1-score is the harmonic mean of the precision and the recall ranging from 0, in the worst case, to 1, at its highest score. Both, accuracy and F1-score are important measurements for the evaluation of classification models (see e.g. [136]). The resulting matrix is presented in 5.8, and shows the accuracy of the decision tree is 99.96%, with only 1 case misclassified out of 2628.

### 5.4.2 33-Bus Test Case

**Table 5.2:** Line parameters of 33-Bus test system

<table>
<thead>
<tr>
<th>Line</th>
<th>R(Ω)</th>
<th>X(mH)</th>
<th>Line</th>
<th>R(Ω)</th>
<th>X(mH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.007</td>
<td>0.015</td>
<td>16</td>
<td>0.056</td>
<td>0.035</td>
</tr>
<tr>
<td>2</td>
<td>0.070</td>
<td>0.040</td>
<td>17</td>
<td>0.035</td>
<td>0.035</td>
</tr>
<tr>
<td>3</td>
<td>0.063</td>
<td>0.035</td>
<td>19</td>
<td>0.077</td>
<td>0.045</td>
</tr>
<tr>
<td>4</td>
<td>0.070</td>
<td>0.060</td>
<td>20</td>
<td>0.084</td>
<td>0.075</td>
</tr>
<tr>
<td>5</td>
<td>0.077</td>
<td>0.065</td>
<td>21</td>
<td>0.112</td>
<td>0.075</td>
</tr>
<tr>
<td>6</td>
<td>0.070</td>
<td>0.040</td>
<td>23</td>
<td>0.007</td>
<td>0.045</td>
</tr>
<tr>
<td>7</td>
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<td>0.040</td>
<td>24</td>
<td>0.014</td>
<td>0.015</td>
</tr>
<tr>
<td>9</td>
<td>0.007</td>
<td>0.005</td>
<td>26</td>
<td>0.021</td>
<td>0.010</td>
</tr>
<tr>
<td>10</td>
<td>0.126</td>
<td>0.070</td>
<td>27</td>
<td>0.077</td>
<td>0.045</td>
</tr>
<tr>
<td>11</td>
<td>0.119</td>
<td>0.105</td>
<td>28</td>
<td>0.154</td>
<td>0.125</td>
</tr>
<tr>
<td>12</td>
<td>0.070</td>
<td>0.045</td>
<td>29</td>
<td>0.077</td>
<td>0.050</td>
</tr>
<tr>
<td>13</td>
<td>0.056</td>
<td>0.055</td>
<td>30</td>
<td>0.154</td>
<td>0.090</td>
</tr>
<tr>
<td>14</td>
<td>0.063</td>
<td>0.035</td>
<td>31</td>
<td>0.042</td>
<td>0.055</td>
</tr>
<tr>
<td>15</td>
<td>0.070</td>
<td>0.045</td>
<td>32</td>
<td>0.035</td>
<td>0.020</td>
</tr>
<tr>
<td>L1</td>
<td>0.315</td>
<td>0.220</td>
<td>L6</td>
<td>0.350</td>
<td>0.240</td>
</tr>
<tr>
<td>L2</td>
<td>0.350</td>
<td>0.215</td>
<td>L7</td>
<td>0.350</td>
<td>0.245</td>
</tr>
<tr>
<td>L3</td>
<td>0.350</td>
<td>0.235</td>
<td>L8</td>
<td>0.301</td>
<td>0.210</td>
</tr>
<tr>
<td>L4</td>
<td>0.350</td>
<td>0.255</td>
<td>L9</td>
<td>0.315</td>
<td>0.215</td>
</tr>
<tr>
<td>L5</td>
<td>0.350</td>
<td>0.255</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Figure 5.9 shows the topology of the modified IEEE 33-Bus islanded system tested in this case study, while Fig. 5.10 gives an example of six possible sets of radial configurations $S = [1, 2, \ldots, s]$ for this test case. Table 5.2 contains the line parameters. In this simulation, DG1 is chosen to be a dispatchable unit (such as a diesel generator), while DG2 (wind turbine), DG3 (wind turbine), and
DG4 (photo-voltaic system) are non-dispatchable RESs.

To train the classifier, an extensive series of power profiles \( F_{d,t} = [P_{1,d,t}, P_{2,d,t}, \ldots P_{n,d,t}] \) are sequentially generated using typical RESs generation profiles. The loading profiles are again assumed to be commercial [134]. For this more complex test system, the decision tree did not show sufficient results. That is why several more elaborate methods have been tested including support vector machines, learning classifier systems, random forests and other ensemble models. The random forest classifier showed the highest accuracy in this case. For a 10-fold cross validation, the accuracy for the random forest classifier was on average 92.88% with a standard deviation of 0.004. The average F1-score is 0.88. However, the misclassified cases were investigated further and showed only minimal changes in terms of the power loss if the predicted configuration was used compared to the optimal one. The confusion matrix on the test set shown in Fig. 5.11 presents the percentages of correctly classified inputs of
each class with respect to the size of the true class labels. Figure 5.12 shows a 48 hours section of the simulation results. During this period, the optimal configurations $G(F_{dt}) = \hat{r} \in [1, 2, .., r]$ is found at eleven different sets of closed switches.

**Figure 5.11:** Resulting confusion matrix of the 33-Bus test system after evaluation.

### 5.5 Interim Conclusion

In this study, we have presented a random forest classifier to optimize reconfigurable islanded AC microgrids. The objective of the classifier is to categorize any load and generation power profile to
find the best topology configuration that minimizes the power loss within the system. The proposed classification system is initially built by generating a training dataset, consisting of an extensive series of power profiles evaluated in a particular islanded AC microgrid model. The training power profiles are sequentially generated using typical time-consistent RESs power generation and load functions, with considerations of seasonality trends reflected on a monthly scale. Once the training dataset is generated, and verified to have feasible solutions considering the system constraints of power generation and voltage and current limits, it is used to build the classifier. To build the decision tree, measurements of data entropy to quantify the quality of a potential rule are used, in order to find the optimal tree that can classify the dataset. Random forest are ensembles of decision trees that in general outperform a single one by training multiple diverse decision trees simultaneously. Both approaches are explored in this study, and posteriorly used to optimize both a 9-Bus and a 33-Bus reconfigurable systems, respectively. The obtained classifiers are then tested in new datasets unknown to the systems, to verify their classification and prediction accuracy in the microgrid models. The results are finally displayed in confusion matrices, proving their feasibility by obtaining accuracies of 99.96% and 92.88%, respectively.

In modern microgrids highly integrated with renewable energy sources, BESSs are widely used due to their load-shifting capabilities. Future work in this regard accounts for the inclusion of BESSs in the problem formulation, considering their SoCs as variables to classify, while their output power to be part of the classifier solution. It is worth noting that BESSs would add another complexity level to the problem due to their dispatchable characteristics, which can be simplified by establishing predefined ranges of rates of charge and discharge. Studies and experiments in this regard are needed in order to find the best problem formulation without compromising the already achieved fast response advantage.
Chapter 6

Conclusions and Future Work

This thesis investigates different hierarchical control techniques and approaches of islanded AC, and hybrid AC/DC microgrids. The introductory review gives a general insight of how vast, complex and interdisciplinary the subject is. The classification of microgrid topologies and control techniques is introduced, while objectives, advantages and drawbacks are highlighted. The mathematical models presented in the subsequent chapters are power level models, and include power devices with different primary level controllers, such as droop-based, constant power, and constant voltage. Islanded AC, and hybrid AC/DC microgrid systems are detailed and modeled, allowing the implementation of the control and optimization approaches proposed afterwards. Droop controlled distributed generators, inverters, inter-linking converters, and battery energy storage systems are considered. A power loss minimization approach based on a perturbation and observation strategy is presented, proved to perform successfully when loads are constant or change slowly over time. This approach is fully distributed, allowing to address a complex secondary level control objective without any type of communication system. Also, a consensus-based distributed control for hybrid AC/DC microgrids is presented, addressing different secondary objectives, such as inter-linking converter power flow control, battery energy storage systems coordination, proportional active power dispatch, and AC sub-grid frequency and average DC voltage restoration. The secondary level control is distributed, and relies on a multi-agent system and a consensus algorithm of the participating units. Finally, a machine learning-based classification system for reconfigurable islanded microgrids is presented. The objective of the classifier is to classify any load and generation power profile, in order to identify the best topology configuration that minimize the power loss within the system. This approach is centralized. Simulation results for every case demonstrate the successful performance of the presented strategies.

In conclusion, the control architectures and optimization objectives of microgrids strongly depend on the type, hardware composition, energy sources, communication network, and the type of information available. Therefore, designing controllers that are able to function seamlessly under a wide range of configurations and circumstances is key to take best advantage of the features of microgrids. There is substantial research work that can be looked into in the future to solidify and improve the proposed control and optimization strategies presented in this thesis. From the point of view of the decentralized secondary control of microgrids, the lack of a communication network limits the capabilities of any control strategy. Hence, any partial or complete characterization of the system can improve dramatically
the decentralized performance. However, this is not easy to achieve, specially for large and complex meshed microgrids. On the other hand, secondary control strategies based on consensus algorithms are proved to be feasible solutions as they combine both the self sufficient autonomous operation capability and the coordinated cooperation to address global objectives. However, these strategies face other problems inherent to the communication network they rely on, such as data integrity and cyber-security risks. Therefore, probabilistic studies regarding communication disruption and data security violations, and the effects on the control strategy, are on the list of future work. Furthermore, distributed tertiary level control based on consensus algorithm is a subject worth of future investigations. Moreover, the use of machine learning-based approaches in power systems (i.e., neural networks, decision trees, learning classifiers systems) allows to address some of the technical challenges of smart grids related to pattern recognition, such as renewable power generation prediction, loading and price forecasting, and system optimization.
References


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