UNIVERSIDADE ESTADUAL DE CAMPINAS
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Sensibility Analysis of Alternating Direction Method of Multipliers Applied to Distributed Energy Management of Microgrids

Análise de Sensibilidade do Método de Direção Alternada de Multiplicadores Aplicado à Gestão de Energia Distribuída de Microrredes

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Supervisor: Prof. Dr. Marcos Julio Rider Flores

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“Quem conduz e arrasta o mundo não são as máquinas, são as ideias ”

(Victor Hugo)

Abstract

The alternating direction method of multipliers (ADMM) can be used to efficiently distribute the centralized energy management system (EMS) of microgrids. However, different configurations and versions of the ADMM can lead to dissimilar performances. Thus, a sensibility analysis is carried out in this paper to determine the best version of the ADMM to be applied as a microgrid controller. In this case, two types of EMSs are modeled via convex optimization and then distributed using the ADMM method: EMS for microgrids with and without the internal network. Both study cases consider distributed energy resources, such as renewable energy sources, direct load control, and battery energy storage systems, and they can be used to operate in either a grid-connected or isolated mode. In order to test the ADMM algorithm, the combination of the following versions have been considered: scaled, unscaled, synchronous, and asynchronous. A sensibility analysis is carried out based on different values of the penalty parameter ρ, aiming to assess its impact on convergence and optimality. Monte Carlo simulations have been deployed to statistically analyze the performance of the algorithms and to achieve insightful conclusions. The results show that the optimality of the problem and the speed of convergence are very dependent on the choice of ρ, but values closer to the unity generate overall better performance. Finally, it has been shown that communication issues could affect the time of convergence, but not the optimality of the ADMM.

Keywords: Alternating direction method of multipliers (ADMM), distributed optimization, energy management system, microgrids, synchronous and asynchronous ADMM.

Resumo

O método de multiplicadores de direção alternada (ADMM) pode ser usado para distribuir com eficiência o sistema de gerenciamento de energia centralizado (EMS) das microrredes. No entanto, diferentes configurações e versões do ADMM podem levar a desempenhos diferentes. Assim, neste trabalho é realizada uma análise de sensibilidade para determinar a melhor versão do ADMM a ser aplicada como controlador de microrrede. Nesse caso, dois tipos de EMSs são modelados via otimização convexa e depois distribuídos pelo método do ADMM: EMS para microrredes com e sem rede interna. Ambos casos de estudo consideram recursos de energia distribuída, como fontes de energia renováveis, controle de carga direto e sistemas de armazenamento de energia de bateria, e podem ser usados para operar em um modo conectado à rede ou isolado. Para testar o algoritmo ADMM, a combinação das seguintes versões foi considerada: escalado, não escalado, síncrono e assíncrono. É realizada uma análise de sensibilidade com base em diferentes valores do parâmetro de penalidade ρ, com o objetivo de avaliar o seu impacto na convergência e otimização. Simulações de Monte Carlo foram implementadas para analisar estatisticamente o desempenho dos algoritmos e para chegar a conclusões perspicazes. Os resultados mostram que a otimalidade do problema e a velocidade de convergência são muito dependentes da escolha do ρ, mas valores mais próximos da unidade geram um melhor desempenho geral. Finalmente, foi demonstrado que problemas de comunicação podem afetar o tempo de convergência, mas não a otimização do ADMM.

Palavras-chaves: Método de Direção Alternada de Multiplicadores (ADMM), otimização distribuída, sistema de gestão de energia, microrredes, ADMM síncrono e assíncrono.

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List of abbreviations and acronyms

ADMM	Alternating Direction Multipliers Method
BESS	Battery Energy Storage System
DER	Distributed Energy Resources
DLC	Direct Load Control
DN	Distribution Network
DR	Demand Response
DG	Distributed Generator
EMS	Energy Management System
RES	Renewable Energy Source
PV	Photovoltaic
POI	Point of Interconnection
PV	Photovoltaic
LP	Linear Programming
QP	Quadratic programming
RE	Relative Error

Contents

1 Introduction

1.1 Motivation

Currently, a transition is being experienced in the energy sector in search of a decentralized, flexible, economic and safe network that is based on renewable sources to face the climate change that we have been experiencing in recent decades. The adoption of renewable energy resources is reflected in the increase in their participation in the world energy matrix, especially driven by the growth of solar and photovoltaic generation, because they are rentable energy sources and and their cost trend with a negative slope in recent years. The Fig. 1.1 shows the constant increase of renewable generation, where it can be seen that in recent years the consumption of renewable generation has increased by almost 8 percent year-on-year.

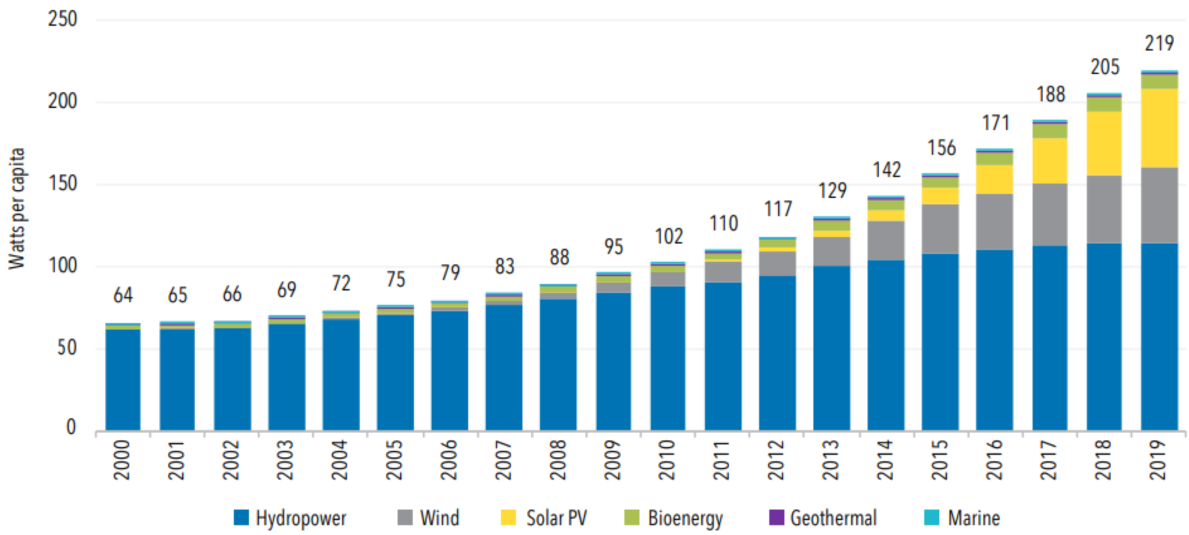

Figure 1.1 – Global renewable electricity consumption by technology.[Source: (IEA et al., 2021)

Renewable energies based on wind and solar sources are an important factor in the transformation of the energy scenario, however, they do not provide flexibility to the system because they are subject to interference. In classic electrical systems the flexibility depends on the generation reserves of hydroelectric and thermal units that can adjust their generation to the variable demand. Despite being a small-scale system, microgrids are a promising solution that addresses this flexibility problem, also they add resilience, reliability, quality, and sustainability of energy to the electricity grid, which reflects their importance in this scenario of energy transition. Thus, these characteristics of improvement to the network provided by the microgrid are due to the fact that it is integrated with distributed energy resources (DERs), such as distributed generation units (DG), controllable loads, energy storage devices, among others.

There are many definitions about microgrid, according to the United States Department of Energy (DOE) a microgrid is "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid . A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode" (DOE, 2011).

An adequate operation is based on the balance between the energy demanded and supplied within it. The increase and development of DERs together with the implementation of advanced metering, monitoring and control systems in last years brings challenges of control and coordination of the microgrid operation (FENG et al., 2018). For a proper operation of microgrids, an efficient and reliable energy management system (EMS) is essential. The EMS monitors the microgrid assets, schedules the operation of the dispatchable DERs, and coordinates the transition from grid-connected to islanded mode, and vice-versa (SU; WANG, 2012),(HATZIARGYRIOU, 2014). Several centralized and non-centralized EMS techniques can be found in the specialized literature (KATIRAEI et al., 2008), (ZIA; ELBOUCHIKHI; BENBOUZID, 2018; OLIVARES; CAñIZARES; KAZERANI, 2011; SILVA et al., 2021), where non-centralized techniques are divided into decentralized and distributed techniques (YAZDANIAN; MEHRIZI-SANI, 2014), (HAN et al., 2018).

1.2 Problem Statement

Traditionally, microgrids use centralized control systems, wherein a unique controller receives, aggregates and processes all data, e.g., power generated by the renewable energy sources (RESs), energy consumption, and energy arbitrage with the main grid, among others. With this information, the central controller optimizes the dispatch of the flexible DERs and makes the most convenient operational decisions, considering energy prices over the long term. Most practical and academic works regarding EMS are focused on this control scheme because it is easy to develop and maintain. Several algorithms based on mathematical programming (HELAL et al., 2017; AMROLLAHI; BATHAEE, 2017; VERGARA et al., 2017; SILVA et al., 2021; GIRALDO et al., 2019; IGUALADA et al., 2014), meta-heuristics (MARZBAND et al., 2017),(MARZBAND et al., 2014), fuzzy logic (CHAOUACHI et al., 2013), genetic algorithms (ELSIED et al., 2016), and neural networks (WANG; HE; DENG, 2019) have been proposed. However, centralized EMSs have shortcomings. The computational burden of central controllers is a concern because all data is processed by a single agent, which has to make all the decisions and broadcast them. Moreover, all DERs must share their information with the central controller, which creates a single point of failure, cyber-attacks and data privacy violations (YAZDANIAN; MEHRIZI-SANI, 2014). Additionally, a microgrid with a large number of spatially dispersed DERs implies a greater investment in the infrastructure for a centralized control and the system communication (FENG et al., 2018). In this context, new control and monitoring techniques based on distributed control have been developed in recent years. Distributed control allows each element or subsystem to make its own decisions without the need for a central coordinator.

Non-centralized controllers do not need a central server because each agent of the system is controlled by its own local controller. A decentralized control scheme lacks communication between agents. In this case, each agent schedules its own operation, regardless of the others. A distributed control scheme, on the other hand, has communication among agents, but not a central server. This allows information to be shared between neighbor agents and improves its performance (HAN et al., 2018). Distributed control offers flexibility, reliability, privacy, and a more robust communication system.

There are several ways to deploy a distributed EMS in microgrids (YAZDANIAN; MEHRIZI-SANI, 2014). One that has been successfully implemented is the multi-agent system (MAS) due to its well-established telecommunication and control architectures that orchestrate independent agents, i.e., DERs (OLIVARES; CAñIZARES; KAZERANI, 2011), (YAZDANIAN; MEHRIZI-SANI, 2014). However, the optimality and feasibility of the MAS operation depends on the algorithm used to deploy it. The most promising MAS techniques are those based on analytical optimization models, such as the alternating direction method of multipliers (ADMM) which guarantee the convergence (BOYD et al., 2011).

Currently, the ADMM is one of the most widely used distributed optimization techniques (LU et al., 2018), it posses a good convergence properties, acceptable accuracy, scalability and robustness (BOYD et al., 2011). Different EMS problems for microgrids have been solved with the ADMM, some of which use it as the main MAS algorithm (ULLAH; PARK, 2019; ZHENG et al., 2018; LIU; GOOI; XIN, 2017). Authors in (LIU et al., 2018; RAJAEI et al., 2021; MOHITI et al., 2019) use the ADMM for multiple microgrids integrated by an AC distribution network. To deal with the uncertainty of RESs, authors in (MA et al., 2018) use an ADMM based on regret minimization. A distributed EMS for network hybrid AC/DC microgrids is developed in (XU et al., 2020). An ADMM applied to distributed EMS considering multiple interconnected microgrids has been formulated in (LIU; GOOI; XIN, 2017), (MANSOUR-SAATLOO et al., 2021; AKULA; SALEHFAR, 2018; NGUYEN; ISHIHARA, 2021). Since the telecommunication among agents might not be perfect, the asynchronous version of the ADMM was proposed in (ULLAH; PARK, 2019) and (ZHENG et al., 2018). Thus, based on the literature review, it is safe to say that the ADMM is suitable for distributed EMS. Regarding the convergence analysis of ADMM and its impact due to the chosen penalty parameter ρ value, few studies have been carried out. The work in (GAO et al., 2018) performed a deterministic analysis of the convergence properties of ADMM applied to distributed EMS in networked microgrids by varying ρ, in (KARGARIAN et al., 2018), the impact of ρ on the convergence of the ADMM applied to optimal power flow in electric power systems was analyzed. New variations of ADMM method were proposed in (SHEN et al., 2020) and (UMER et al., 2021), studying the effect of the tuning parameter ρ on its convergence, futhermore, (UMER et al., 2021) performed an analysis with complete and incomplete communication. However, there is still a lack of conciseness about which type of ADMM is better for different EMS configurations and, more importantly, what the impact of the penalty parameter ρ (used in all versions of the ADMM algorithm) is on the performance of the EMS, both in terms of convergence and optimality.

In this sense, this thesis focuses on the sensibility analysis of the ADMM method applied to distributed EMS. The sensibility analysis is carried out based on different values of the penalty parameter ρ, aiming to assess its impact on convergence and optimality, thus determining the most suitable configuration and type of ADMM to be used as the distributed EMS algorithm.

1.3 Objectives

The dissertation's main goal is to develop an optimization model based on distributed control using a combination of ADMM method versions: scaled, unscaled, synchronous, and asynchronous for the EMS in micrograms in order to perform a sensitivity analysis of the ADMM method. To reach this goal, the following partial objectives are proposed:

- To develop two suitable mathematical models of EMS in microgrids in a centralized form: one that is an EMS based on devices and energy balance, disregarding the internal network, and another that considers the network that interconnects the DERs within the microgrid.
- To distribute the two centralized models using scaled, unscaled, synchronous, and asynchronous ADMM. For each configuration and model, the impact of using dissimilar values of ADMM the penalty parameter ρ will be empirically studied.
- To perform a statistical analysis using Monte Carlo simulations to asses the convergence and optimal of the ADMM-based EMS under demand, renewable and prices uncertainty, validating which is the most practical and efficient way to distribute the EMS microgrid through the ADMM , considering or disregarding the internal network.

1.4 Contributions

The main contributions of this thesis are explicitly as follow:

1. Formulation of optimization models based on distributed control using a combination of ADMM method versions: scaled, unscaled, synchronous, and asynchronous for the EMS in microgrid.
2. Even though ADMM has been used in the past to distribute the EMS of microgrids, to the best of our knowledge, this is the first work that analyses the statistical performance of different types of ADMM via sensibility analysis and Monte Carlo simulations.

1.5 Thesis Outline

The outline of this thesis is as follows:

In Chapter 2: Two EMSs for microgrids are presented and formulated through centralized mathematical optimization models.

In Chapter 3: A review of the ADMM algorithm is presented in order to show the state of art.

In Chapter 4: Analyze diverse versions of ADMM when used as the main algorithm for solving both EMS formulations.

In Chapter 5: Simulations and results are presented. In order to test the effectiveness of the ADMM algorithms and to perform a sensibility analysis, the two types of EMS for the microgrids.

Finally, conclusions and future works are addressed in *Chapter 6*.

2 Proposed Centralized Mathematical Programming Model

Notation

Sets:

$\mathcal{N}$	Set of nodes
$\mathcal{E}$	Set of branches
$\mathcal{N}_g$	Set of distributed generators (DG)
$\mathcal{N}_b$	Set of battery energy storage systems (BESS)
$\mathcal{N}_i$	Set of demand response agents (DR)
$\mathcal{E}_i$	Set of branches connected to node i

Indexes:

i	Node (Bus "From") $i \in \mathcal{N}$
j	Node (Bus "To") $j \in \mathcal{N}$
ij	Circuit (Branch) $ij \in \mathcal{E}$

Parameters:

Δ_t	Duration of each load level [h]
η_c	Cost of BESS aging [m.u./kW]
η_{inc}	Cost of DR incentives [m.u./kW^2]
η_{loss}	Cost of BESS losses [m.u./kW^2]
η_p	Cost of BESS utilization [m.u./kW]
m_{inc}	Constant DR incentives [m.u.]
$\overline{E}_{BESS}$	Maximum energy of the BESS [kWh]
$\overline{f}_{j \to h}$	Maximum power flow at the branch $j \to h$ [kW]
$\overline{P}_{DLC}$	Maximum direct load control (DLC) power [kW]
$\overline{P}_{BESS}$	Maximum injection/extraction of the BESS [kW]

$\overline{P}_{PV}$	Constant PV generation [kW]
$\overline{P}_i$	Maximum injected power by the distributed energy resource (DER) [kW]
$\overline{P}_{MG}$	Maximum active power exchanged with the distribution network [kW]
$\underline{f}^{j\to h}$	Minimum power flow at the branch $j \to h$ [kW]
$\underline{P}_i$	Minimum injected power by the DER [kW]
a_i	DG quadratic cost [m.u./kW^2]
b_i	DG linear cost [m.u./kW]
c_i	DG constant cost [m.u.]
C_0	Electricity price at the point of interconnection (POI) with the distribution network [m.u./kWh]
C_{DLC}	Penalization cost of DLC [m.u./kWh]
C_l	Price of demand shedding [m.u./kWh]
C_p	Price of purchasing energy from the main grid [m.u./kWh]
C_s	Price of selling energy to the main grid [m.u/kWh]
$d_i^{j\to h}$	Parameter that indicates the direction of the power flow at the branch $j \to h$
E_{BESS}^0	Initial state of charge of the BESS [kW]
$\overline{P}_{MG}$	Maximum power transference of the microgrid [kW]

Continuous variables:

E_{BESS}	State of charge of the BESS [kWh]
$f^{j\to h}$	Power flow at branch $j \to h$ [kW]
P_{DLC}	Non-essential demand that can be reduced via DLC [kW]
P_{BESS}	Charging/discharging power of the BESS [kW]
P_i	Active power injected/extracted by the DER at node i [kW]
P_s	Active power sold to the main grid [kW]
P_p	Active power supplied by main grid [kW]

2.1 Introduction

In this chapter, two EMSs for microgrids are presented and formulated through centralized mathematical optimization models. The first model is an EMS based on devices and energy balance, disregarding the internal network. The second model, on the other hand, does consider the network and the DERs are located along the nodes. The first model is suitable for small-scaled applications (e.g., smart-homes, nanogrids, etc), whereas the second model is suitable for complex microgrids composed of numerous DERs.

The rest of the chapter is organized as follows: Section 2.2 describes the formulation and modeling of a device-based centralized EMS. Section 2.3 describes the formulation and modeling of a centralized EMS considering the internal network. Finally, Section 2.4 contains a summary of the chapter.

2.2 Centralized EMS based on devices

In this model, the DERs of a small microgrid (e.g., a smart-home) are controlled by an EMS. The smart-home can purchase or sell energy directly from the distribution network. It is composed of a rooftop PV generator, a DLC scheme for non-essential loads and a BESS. Excess energy can be stored in the BESS for use at a suitable future time.

For these small-scaled applications, the objective is to minimize the operational cost given by (2.1), which avoids the purchase of energy from the distribution network and maximizes its sale, as well as avoiding a penalty for not supplying energy to the DLC demand, where C_p is the price of purchasing energy from the DN, in m.u./kWh; C_s is the price of selling energy to the DN in m.u/kWh; and C_{DLC} is the price of reducing any DLC demand, in m.u/kWh. The EMS based on devices is formulated for one time interval Δ_t and is given by constraints (2.1)–(2.8).

$$\min \{\Delta_t C_p P_p - \Delta_t C_s P_s - \Delta_t C_{DLC} P_{DLC}\} \tag{2.1}$$

subject to:

$$P_p + P_{PV} - P_d - P_{BESS} - P_s - P_{DLC} = 0 \tag{2.2}$$

$$E_{BESS} = E^0_{BESS} + \Delta_t P_{BESS} \tag{2.3}$$

$$0 \leq P_p \leq \overline{P}_{MG} \tag{2.4}$$

$$0 \leq P_s \leq \overline{P}_{MG} \tag{2.5}$$

$$0 \leq P_{DLC} \leq \overline{P}_{DLC} \tag{2.6}$$

$$-\overline{P}_{BESS} \leq P_{BESS} \leq \overline{P}_{BESS} \tag{2.7}$$

$$0 \leq E_{BESS} \leq \overline{E}_{BESS} \tag{2.8}$$

The above formulation described in (2.1)–(2.8) is a linear programming model, where (2.2) is the active power balance at the smart home. Constraint (2.3) calculates the energy of the battery (E_{BESS}) in kWh, considering ideal efficiency and Δ_t is the duration of each time-step in hours. Constraints (2.4) and (2.5) define the power limits to be exchanged with the main grid. Constraint (2.6) limits the amount of demand that can be reduced via DLC, while (2.7) limits by $\overline{P}^{BESS}$ the power injection and extraction from the BESS, positive values of P_{BESS} indicate loading and negative values indicate unloading. Finally, constraint (2.8) limits the BESS capacity.

Note that the linear formulation for this optimization problem is convex, thus ensuring the optimal solution. In addition, this model can be distributed through the ADMM, since from the perspective that each device in the smart home can be considered as an autonomous agent.

2.3 Centralized EMS considering the internal network

This model is based on (ZHENG et al., 2018). The purpose is to optimally schedule the DERs within the microgrid, such as dispatchable DGs, BESSs, and loads/RESs, with and without DR capabilities (a.k.a., prosumers) for a single time interval. These DERs are interconnected by an internal network, modeled using a simplified network flow.

Each DER is associated with a cost function, as shown in (2.9)-(2.11):

For DG agents, a quadratic cost function that represents the energy cost of thermal generators (2.9) is used, where a_i, b_i, c_i are generation cost parameters :

$$C_i\left(P_i\right) = a_i P_i^2 + b_i P_i + c_i \qquad \forall i \in \mathcal{N}_g \quad (2.9)$$

The operational cost of the BESS agents is represented by (2.10), in which the utilization (η_p), degradation (η_c), and efficiency (η_{loss}) cost coefficients are related to the BESS dispatch (ZHENG et al., 2018):

$$C_i\left(P_i\right) = \eta_p P_i + \eta_c \left\| P_i \right\| + \eta_{loss} P_i^2 \qquad \forall i \in N_b \quad (2.10)$$

For prosumers, the cost of participating in DR programs is based on incentives as in (2.11), where m_{inc} is the constant incentive and η_{inc} is the variable incentive.

$$C_i\left(P_i\right) = m_{inc} + \eta_{inc} P_i^2 \qquad \forall i \in N_d \quad (2.11)$$

In addition, the energy exchange between the microgrid and the main grid is taken into account using the price of the electricity C_0 and the power exported at the point of interconnection (POI) via $P_0 = \sum_{i \in N} P_i$. In this way, the objective function (2.12) minimizes the total energy cost for the microgrid. The complete optimization problem is shown in (2.12)–(2.15).

$$\min_{P_i} \left\{ \sum_{i \in N} \left[C_i \left(P_i \right) - C_0 \left(P_i \right) \right] \right\} \tag{2.12}$$

subject to:

$$P_i = \sum_{j \to h \in E_i} d_i^{j \to h} f^{j \to h} \qquad \forall\ i \in \mathcal{N} \tag{2.13}$$

$$\underline{P}_i \leq P_i \leq \overline{P}_i \qquad \forall i \in \mathcal{N} \tag{2.14}$$

$$\underline{f}^{j \to h} \leq f^{j \to h} \leq \overline{f}^{j \to h} \qquad \forall j \to h \in \mathcal{E} \tag{2.15}$$

The above formulation described in (2.12)–(2.15) is a quadratic programming model, where (2.13) represents the active power balance per node, where $d_i^{j \to h}$ is a parameter that indicates the direction of the power flow at the branch $j \to h$, either positive or negative. For simplicity, voltage in buses, active power losses, reactive flow and three-phase electrical network model are not taken into account in this formulation, but they will be considered in future works. Constraint (2.14) limits the injection of active power from DERs at each node, and (2.15) limits the power flow through the branches.

Note that the quadratic formulation for this optimization problem is also convex, thus ensuring the optimal solution. In addition, this model can be distributed through the ADMM, treating each node in the internal network as an autonomous agent.

Note that the two EMS models are convex optimization problems: the model formulated by (2.1)–(2.8) is a linear programming problem, and the model formulated by (2.9)-(2.15) is a quadratic programming problem. Both models can be distributed through the ADMM.

2.4 Summary

In this chapter, two centralized mathematical programming models: Linear Programming (LP) and Quadratic programming (QP) were proposed to solve EMS problem applied to microgrids. The two models are convex optimization problems, thus, guaranteeing the optimal global solution. Both models are suitable to be distributed through the ADMM method.

3 Alternating Direction Method of Multipliers Algorithm

3.1 Introduction

The ADMM method is a very popular and powerful algorithm that solves convex optimization problems in a distributed manner. ADMM was first introduced in the mid-1970s by (GLOWINSKI; MARROCO, 1975), (GABAY; MERCIER, 1976), studied in the 1980s, and by the mid-1990s many theoretical conclusions had been established. In 2011, the method became popular through publication (BOYD et al., 2011), and since then it has been widely applied in wireless sensor networks, machine learning, and electrical power system. Currently, the ADMM is one of the most widely used distributed optimization techniques (LU et al., 2018), it posses a good convergence properties, acceptable accuracy, scalability, robustness and has a an important role in ensuring data privacy (BOYD et al., 2011) .

The ADMM algorithm is a iterative process based on a decomposition- coordination, it consists of dividing the global problem into subproblems (sorted by regions, elements, units, etc.) where each subproblem is easier to deal with, moreover, the procedure that follows the solution of the subproblems is in such a way that the general process converges to the global optimum of the original problem (BOYD et al., 2011).

There are two types of variables in the ADMM method, local variables and consensus variables (PUTRATAMA et al., 2021), local variables are obtained through measurements or computational methods and they are only known by their own agent, thus, different agents have different local variables. On the other hand, the consensus variables are those that are shared between several agents, these variables are obtained and updated in each iteration of the ADMM algorithm process where communication and coordination between each agent and its neighbors is required.

The ADMM method and its versions used in this work are the unscaled, scaled,synchronous, and asynchronous versions.

The rest of the chapter is organized as follows: Section 3.2 presents the Unscaled ADMM. Section 3.3 describes the Scaled ADMM, Section 3.4 presents the Synchronous ADMM, Section 3.5 presents the Asynchronous ADMM. Finally, Section 3.6contains a summary of the chapter.

3.2 Unscaled ADMM

The ADMM method introduces copies of coupling variables for each area to decouple the coupling constraints, while enforcing agreement between the copies of the coupling variables using consistency constraints

This is the most basic version, in which the ADMM is used to solve the following type of optimization problems:

$$\begin{aligned} \min_{x,z} \quad & f(x) + g(z) \\ \text{subject to: } & Ax + Bz = c \end{aligned} \tag{3.1}$$

where the functions f and g are convex, variables $x \in \mathbb{R}^n$ and $z \in \mathbb{R}^m$, and parameters $A \in \mathbb{R}^{p\times n}$, $B \in \mathbb{R}^{p\times m}$, and $c \in \mathbb{R}^p$. The augmented Lagrangian of (3.1) is given by (3.2).

$$L_\rho(x, z) = f(x) + g(z) + \lambda^T(Ax + Bz - c) \; + (\rho/2) \left\|Ax + Bz - c\right\|_2^2 \tag{3.2}$$

where $\rho > 0$ is the penalty parameter and $\lambda \in \mathbb{R}^p$ is the dual variable. The ADMM algorithm consists of updating the primal variables, x and z, and the dual variable λ iteratively, as shown in (3.3a)–(3.3c).

$$x^k = \text{argmin}_x L_\rho(x, z^{k-1}, \lambda^{k-1}) \tag{3.3a}$$

$$z^k = \text{argmin}_z L_\rho(x^k, z, \lambda^{k-1}) \tag{3.3b}$$

$$\lambda^k = \lambda^{k-1} + \rho(Ax^k + Bz^k - c) \tag{3.3c}$$

where k is the iteration. The algorithm will iterate until a given convergence criterion is satisfied. The convergence conditions are given by the primary and dual residuals, $\varepsilon_{\text{primal}}$ and $\varepsilon_{\text{dual}}$, in (3.4) and (3.5), respectively.

$$\varepsilon_{\text{primal}} = ||Ax^k + Bz^k - c||_2^2 \tag{3.4}$$

$$\varepsilon_{\text{dual}} = ||\lambda^k - \lambda^{k-1}||_2^2 \tag{3.5}$$

The ADMM ends when both residuals $\varepsilon_{\text{primal}}$, and $\varepsilon_{\text{dual}}$, are lower than a given convergence tolerance ϵ. Under convex conditions of the original problem (3.1), and disregarding computational approximation errors, the final solution is shown to be optimal (BOYD et al., 2011).

3.3 Scaled ADMM

In this case, the dual variables are scaled by making $u = (1/\rho)\lambda$. Then, replacing λ with u and combining the linear and quadratic terms in (3.2), the augmented Lagrangian is rewritten as shown in (3.6).

$$L_\rho(x, z, u, \rho) = f(x) + g(z) + (\rho/2)\|Ax + Bz - c + u\|_2^2 + \text{const.} \tag{3.6}$$

Thus, the scaled ADMM algorithm consists of the following updates, as shown in (3.7a)–(3.7c).

$$x^k = \text{argmin}_x \left\{ f(x) + (\rho/2)\left\|Ax + Bz^{k-1} - c + u^{k-1}\right\|_2^2 \right\} \tag{3.7a}$$

$$z^k = \text{argmin}_z \left\{ g(z) + (\rho/2)\left\|Ax^k + Bz - c + u^{k-1}\right\|_2^2 \right\} \tag{3.7b}$$

$$u^k = u^{k-1} + Ax^k + Bz^k - c \tag{3.7c}$$

In general, the scaled form is shorter than the unscaled form, and can be computationally advantageous when the dual variables take large values (BOYD et al., 2011).

3.4 Synchronous ADMM

Being ADMM a iterative method, it requires synchronized communication among all the controller units of the system. Thus, this type of ADMM considers a communication scenario in which the exchange of information among neighboring agents is ideal. Hence, the synchronous ADMM is the same as implementing either (3.3a)–(3.3c) or (3.7a)–(3.7c), without delays.

3.5 Asynchronous ADMM

This concept was introduced in (WEI; OZDAGLAR, 2013). In a heterogeneous system, each local problem may have a different computational time, so some units must wait to receive information from a slower unit and thus be able to proceed to the next iteration. Also, there may be delays or failures in the communication or retransmission of messages. Thus, asynchronous ADMM considers that the communication between agents might be far from ideal.

In this way, the values of x^k, y^k, and λ^k in (3.3a)–(3.3c) and of x^k, y^k, and u^k in (3.7a)–(3.7c) are not updated with the latest information, causing the ADMM to use old values at each agent.

Fig. 3.1 show how the ADMM behaves with synchronous and asynchronous communication assuming three controller units that interact with each other. It is observed in Fig. 3.1-(a) that to start the next iteration, the local problems of all agents must have been processed and therefore have shared their updated local information with the neighboring agents. On the other hand, Fig. 3.1-(b) shows delays or advances in the processing of each local problem by iteration, and for the next iteration there is not the necessity to have the information of the neighboring units updated.

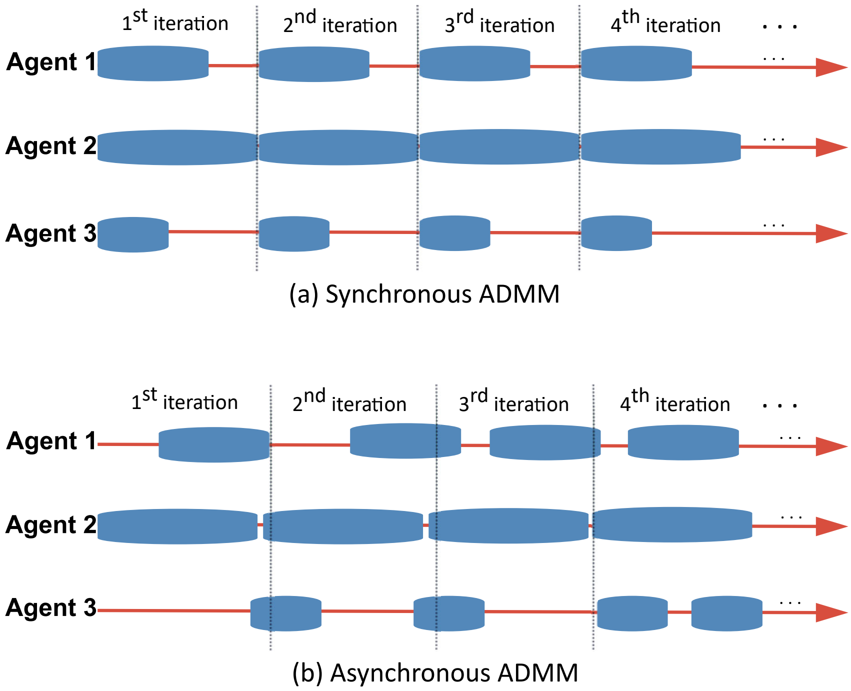

Figure 3.1 – Illustrative example of synchronous and asynchronous ADMM [Source: adapted from (GUO; HUG; TONGUZ, 2017)]

3.6 Summary

In this chapter, the ADMM algorithm that solves convex optimization problems by breaking them into smaller pieces was presented, including a basic convergence theorem, some variations on the basic version that are useful in practice. These variations are: Unscaled ADMM, the elemental version of representing the ADMM; Scaled ADMM, another way of representing the ADMM obtained by scaling the dual variables; Synchronous ADMM, to be used in case of having an ideal communication system; Asynchronous ADMM, willing to deal with communication problems that arise in the system.

4 Transition from Centralized to Distributed EMS

4.1 Introduction

The purpose of this section is to analyze diverse versions of ADMM when used as the main algorithm for solving both EMS formulations presented in Section 3. In this section, models (2.1)–(2.8) and (2.9)–(2.15) are distributed in such a way that each agent is a DER of the microgrid, taking into account that communication exists between agents, but each one of them must optimize its own subproblem.

4.2 EMS based on devices

As the first part of the methodology, it is necessary to consider that the system developed to solve the EMS problem based on devices is a multi-agent system, each agent processing its own information and the information obtained from the interaction with neighboring agents, taking the best operating decision. Thus, for the distribution of the model presented in the subsection 2.2, the BESS, DLC and POI were considered as agents.

To the distribute the EMS based on devices model, the global problem formulated in (2.1)–(2.8) is divided into local problems, each local problem is associated with an agent (BESS, DLC or POI). Therefore, each local problem must be subject to the agent's own objectives and constrain, however (2.2) is the only complicating constraint that couples variables from different agents. Thus, auxiliary copies are created for these variables: $P_{DLC}^{\mathrm{aux}_1}$, $P_{DLC}^{\mathrm{aux}_3}$, $P_{BESS}^{\mathrm{aux}_1}$, $P_{BESS}^{\mathrm{aux}_2}$, and, consequently, its respective equality constraints (4.1)–(4.2) are introduced, where λ_{BESS} and λ_{DLC} are dual variables associated with each restriction. Constrains (2.2), (2.3), (2.6), and (2.7) are rewritten as shown in (4.3)–(4.6).

$$P_{BESS}^{\mathrm{aux}_1} = P_{BESS}^{\mathrm{aux}_2} : \lambda_{BESS} \tag{4.1}$$

$$P_{DLC}^{\mathrm{aux}_1} = P_{DLC}^{\mathrm{aux}_3} : \lambda_{DLC} \tag{4.2}$$

$$P_p + P_{PV} - P_d - P_{BESS}^{\mathrm{aux}_1} - P_s - P_{DLC}^{\mathrm{aux}_1} = 0 \tag{4.3}$$

$$E_{BESS} = E_{BESS}^0 + \Delta_t P_{BESS}^{\mathrm{aux}_2} \tag{4.4}$$

$$-\overline{P}_{BESS} \leq P_{BESS}^{\mathrm{aux}_2} \leq \overline{P}_{BESS} \tag{4.5}$$

$$0 \leq P_{DLC}^{\mathrm{aux}_3} \leq \overline{P}_{DLC} \tag{4.6}$$

For the constrains above (4.1)–(4.6), it is observed that state and control variables can be redefined for each agent: BESS ($P_{BESS}^{\text{aux}_2}$, E_{BESS}), DLC ($P_{DLC}^{\text{aux}_3}$) and POI (P_p, P_d, $P_{BESS}^{\text{aux}_1}$, $P_{DLC}^{\text{aux}_1}$). However, the model is not distributed due to the presence of the equality constrains of the auxiliary variables introduced (4.1)–(4.2). Therefore, as previous step of the unscaled ADMM algorithm, through the Augmented Lagrangian, the constrains (4.1)–(4.2) are added to the objective function (2.1) multiplied by their respective dual variable (λ_{BESS}, λ_{DLC}) and the ADMM penalty parameter (ρ). Thus, the original model can be expressed as follows:

$$\begin{aligned} \min \{ & C_p P_p - C_s P_s + C_{DLC} P_{DLC} \\ & + \lambda_{BESS} \left(P_{BESS}^{\text{aux}_1} - P_{BESS}^{\text{aux}_2} \right) + \rho/2 \left(P_{BESS}^{\text{aux}_1} - P_{BESS}^{\text{aux}_2} \right)^2 \\ & + \lambda_{DLC} (P_{DLC}^{\text{aux}_1} - P_{DLC}^{\text{aux}_3}) + \rho/2 \left(P_{DLC}^{\text{aux}_1} - P_{DLC}^{\text{aux}_3} \right)^2 \} \end{aligned} \tag{4.7}$$

Subject to: (2.4), (2.5), (2.8), (4.3)–(4.6).

For the proposed model, a communication system is considered in such a way that only the POI agent interacts with the BESS and DLC agents, excluding a possible interaction between the BESS and DLC agents. Consequently, the above model (4.7) can already be distributed using unscaled ADMM, where, in the iteration k it can be decomposed into three subproblems, each subproblem per agent, as follows:

For the POI:

$$\begin{aligned} \min_{P_{BESS}^{\text{aux}_1}, P_{DLC}^{\text{aux}_1}} \Big\{ & C_p P_p - C_s P_s + \lambda_{BESS}^{k-1} \left(P_{BESS}^{\text{aux}_1} - P_{BESS}^{\text{aux}_2,k-1} \right) + \rho/2 \left(P_{BESS}^{\text{aux}_1} - P_{BESS}^{\text{aux}_2,k-1} \right)^2 \\ & + \lambda_{DLC}^{k-1} (P_{DLC}^{\text{aux}_1} - P_{DLC}^{\text{aux}_3,k-1}) + \rho/2 \left(P_{DLC}^{\text{aux}_1} - P_{DLC}^{\text{aux}_3,k-1} \right)^2 \Big\} \end{aligned} \tag{4.8}$$

Subject to: (2.4), (2.5), (4.3).

For the BESS:

$$\min_{P_{BESS}^{\text{aux}_2}} \left\{ \lambda_{BESS}^{k-1} \left(P_{BESS}^{\text{aux}_1,k-1} - P_{BESS}^{\text{aux}_2} \right) + \rho/2 \left(P_{BESS}^{\text{aux}_1,k-1} - P_{BESS}^{\text{aux}_2} \right)^2 \right\} \tag{4.9}$$

Subject to: (2.8), (4.4), (4.5).

For the DLC:

$$\min_{P_{DLC}^{\text{aux}_3}} \left\{ C_{DLC} P_{DLC}^{\text{aux}_3} + \lambda_{DLC}^{k-1} (P_{DLC}^{\text{aux}_1,k-1} - P_{DLC}^{\text{aux}_3}) + \rho/2 \left(P_{DLC}^{\text{aux}_1,k-1} - P_{DLC}^{\text{aux}_3} \right)^2 \right\} \tag{4.10}$$

Subject to: (4.6).

For a more straightforward representation (4.7) is expressed in a reduced form, given by $F\left(Y, X_1, X_2, X_3, \Lambda\right)$. For the established sets in (4.11a)–(4.11e): X_1, X_2, and X_3 are sets that contain the coupling variables between the agents, Y is the set that contains the primal variables and Λ is the set that contains dual variables.

$$X_1 = [P_{BESS}^{\mathrm{aux}_1},\, P_{DLC}^{\mathrm{aux}_1}] \tag{4.11a}$$

$$X_2 = [P_{BESS}^{\mathrm{aux}_2}] \tag{4.11b}$$

$$X_3 = [P_{DLC}^{\mathrm{aux}_3}] \tag{4.11c}$$

$$Y = [P_p,\, P_s,\, E_{BESS}] \tag{4.11d}$$

$$\Lambda = [\lambda_{BESS},\, \lambda_{DLC}] \tag{4.11e}$$

Then, having the distributed model, the process for deploying the unscaled synchronous ADMM is given by Algorithm 1. By using scaled ADMM, each agent will solve its own optimization and transfer the exchange variable with neighbor agent until convergence. In this process, at the k-th iteration, X_1^k, X_2^k, X_3^k and Λ^k, are considered parameters.

For the distributed problem throught unscaled ADMM in Algorithm 1, if there is a failure in the exchange of information between neighbor agents after the iteration the k, for the next iteration $k+1$ the value of coupled variables will not be updated and the last stored value will be used, that is, the value obtained in the previous iteration $k-1$. The process for deploying the unscaled asynchronous ADMM is given by Algorithm 2.

Algoritmo 1: Unscaled synchronous ADMM for a EMS based on devices

Step 1: Initialization
$k \leftarrow 0$
$X_1^k \leftarrow 0, X_2^k \leftarrow 0, X_3^k \leftarrow 0, \Lambda^k \leftarrow 1$
Step 2: Subproblem for each agent
$k \leftarrow k+1$
for *each agent* **do**
  if *agent is the POI* **then**
    $X_1^k = \text{argmin}_{X_1} F\left(Y, X_1, X_2^{k-1}, X_3^{k-1}, \Lambda^{k-1}\right)$
    s.t.: (2.4), (2.5) and (4.3).
  end
  if *agent is the BESS* **then**
    $X_2^k = \text{argmin}_{X_2} F\left(Y, X_1^{k-1}, X_2, X_3^{k-1}, \Lambda^{k-1}\right)$
    s.t.: (2.8), (4.4) and (4.5).
  end
  if *agent is the DLC* **then**
    $X_3^k = \text{argmin}_{X_3} F\left(Y, X_1^{k-1}, X_2^{k-1}, X_3, \Lambda^{k-1}\right)$
    s.t.: (4.6).
  end
  $Z = [P_{BESS}^{\text{aux}_2}, P_{DLC}^{\text{aux}_3}]$
end
Step 3: Update dual variables
  $\Lambda^k = \Lambda^{k-1} + \rho(X_1^k - Z^k)$
Step 4: Convergence test
if $\sum \left|X_1^k - Z^k\right| \leq \epsilon$ *and* $\sum \left|\Lambda^k - \Lambda^{k-1}\right| \leq \epsilon$ **then**
  End algorithm
else
  Return to Step 2
end

Algoritmo 2: Unscaled asynchronous ADMM for a EMS based on devices

Step 1: Initialization
$k \leftarrow 0$
$X_1^k \leftarrow 0, X_2^k \leftarrow 0, X_3^k \leftarrow 0, \Lambda^k \leftarrow 1$
Step 2: Subproblem for each agent
$k \leftarrow k+1$
for *each agent* **do**
  if *communication with neighbor devices is successful* **then**
    if *agent is the POI* **then**
      $X_1^k = \text{argmin}_{X_1} F\left(Y, X_1, X_2^{k-1}, X_3^{k-1}, \Lambda^{k-1}\right)$
      s.t.: (2.4), (2.5) and (4.3).
    end
    if *agent is the BESS* **then**
      $X_2^k = \text{argmin}_{X_2} F\left(Y, X_1^{k-1}, X_2, X_3^{k-1}, \Lambda^{k-1}\right)$
      s.t.: (2.8), (4.4) and (4.5).
    end
    if *agent is the DLC* **then**
      $X_3^k = \text{argmin}_{X_3} F\left(Y, X_1^{k-1}, X_2^{k-1}, X_3, \Lambda^{k-1}\right)$
      s.t.: (4.6).
    end
  else
    $X_i^k \leftarrow X_i^{k-1}$
  end
  $Z = [P_{BESS}^{\text{aux}_2}, P_{DLC}^{\text{aux}_3}]$
end
Step 3: Update dual variables
  $\Lambda^k = \Lambda^{k-1} + \rho(X_1^k - Z^k)$
Step 4: Convergence test
if $\sum \left|X_1^k - Z^k\right| \leq \epsilon$ *and* $\sum \left|\Lambda^k - \Lambda^{k-1}\right| \leq \epsilon$ **then**
  End algorithm
else
  Return to Step 2
end

Rewriting the distributed EMS based on devices via unscaled synchronous ADMM into scaled synchronous ADMM, the dual variables are scaled in the following way: $u_{BESS} = \lambda_{BESS}/\rho$ and $u_{DLC} = \lambda_{DLC}/\rho$. Thus, scaling the dual variable and combining the linear and quadratic terms in the augmented Lagrangian (4.7), (4.12) is obtained :

$$\begin{aligned} \min \{ & C_p P_p - C_s P_s - C_{DLC} P_{DLC} \\ & +\rho/2 \left(P_{BESS}^{\text{aux}_1} - P_{BESS}^{\text{aux}_2} + u_{BESS}\right) - \rho/2 \left(u_{BESS}\right)^2 \\ & +\rho/2 \left(P_{DLC}^{\text{aux}_1} - P_{DLC}^{\text{aux}_3} + u_{DLC}\right) - \rho/2 \left(u_{DLC}\right)^2 \} \end{aligned} \tag{4.12}$$

Consequently, the augmented Lagrangian (4.12) subject to the constrains (2.4), (2.5), (2.8), (4.3)–(4.6) is decomposed through scaled ADMM. In the iteration k of the algorithm three subproblems are obtained, each one per agent as follows:

For the POI:

$$\begin{aligned} \min_{P_{BESS}^{\text{aux}_1}, P_{DLC}^{\text{aux}_1}} \Big\{ & C_p P_p - C_s P_s + \rho/2 \left(P_{BESS}^{\text{aux}_1} - P_{BESS}^{\text{aux}_2,k} + u_{BESS}^k\right) - \rho/2 \left(u_{BESS}^k\right)^2 \\ & \rho/2 \left(P_{DLC}^{\text{aux}_1} - P_{DLC}^{\text{aux}_3,k} + u_{DLC}^k\right) - \rho/2 \left(u_{DLC}^k\right)^2 \Big\} \end{aligned} \tag{4.13}$$

Subject to: (2.4), (2.5), (4.3).

For the BESS:

$$\min_{P_{BESS}^{\text{aux}_2}} \left\{ \rho/2 \left(P_{BESS}^{\text{aux}_1,k} - P_{BESS}^{\text{aux}_2} + u_{BESS}^k\right) - \rho/2 \left(u_{BESS}^k\right)^2 \right\} \tag{4.14}$$

Subject to: (2.8), (4.4), (4.5).

For the DLC:

$$\min_{P_{DLC}^{\text{aux}_3}} \left\{ C_{DLC} P_{DLC} + \rho/2 \left(P_{DLC}^{\text{aux}_1,k} - P_{DLC}^{\text{aux}_3} + u_{DLC}^k\right) - \rho/2 \left(u_{DLC}^k\right)^2 \right\} \tag{4.15}$$

Subject to: (4.6).

Same as unscaled ADMM, (4.12) is expressed in a reduced form, given by $G(Y, X_1, X_2, X_3, U)$, where U_k. is the set that contains the scaled dual variables.

$$U = [u_{BESS}, u_{DLC}] \tag{4.16a}$$

Following the same logic as the unscaled synchronous and asynchronous unscaled ADMM, the process for deploying the synchronous and asynchronous scaled ADMM is given by Algorithm 3 and Algorithm 4, considering that at the k-th iteration, X_1^k, X_2^k, X_3^k, Λ^k, and U^k are considered parameters.

Algoritmo 3: Scaled synchronous ADMM for a EMS based on devices

Step 1: Initialization
$k \leftarrow 0$
$X_1^k \leftarrow 0, X_2^k \leftarrow 0, X_3^k \leftarrow 0, U^k \leftarrow 1/\rho$
Step 2: Subproblem for each agent
$k \leftarrow k+1$
for *each agent* **do**
    if *agent is the POI* **then**
        $X_1^k = \mathrm{argmin}_{X_1} G\left(Y, X_1, X_2^{k-1}, X_3^{k-1}, U^{k-1}\right)$
        s.t.: (2.4), (2.5) and (4.3).
    end
    if *agent is the BESS* **then**
        $X_2^k = \mathrm{argmin}_{X_2} G\left(Y, X_1^{k-1}, X_2, X_3^{k-1}, U^{k-1}\right)$
        s.t.: (2.8), (4.4) and (4.5).
    end
    if *agent is the DLC* **then**
        $X_3^k = \mathrm{argmin}_{X_3} G\left(Y, X_1^{k-1}, X_2^{k-1}, X_3, U^{k-1}\right)$
        s.t.: (4.6).
    end
    $Z = [P_{BESS}^{\mathrm{aux}_2}, P_{DLC}^{\mathrm{aux}_3}]$
end
Step 3: Update dual variables
    $U^k = U^{k-1} + (X_1^k - Z^k)$
Step 4: Convergence test
if $\sum \left| X_1^k - Z^k \right| \leq \epsilon$ *and* $\sum \left| U^k - U^{k-1} \right| \leq \epsilon$ **then**
    End algorithm
else
    Return to Step 2
end

Algoritmo 4: Scaled asynchronous ADMM for a EMS based on devices

Step 1: Initialization
$k \leftarrow 0$
$X_1^k \leftarrow 0, X_2^k \leftarrow 0, X_3^k \leftarrow 0, U^k \leftarrow 1/\rho$
Step 2: Subproblem for each agent
$k \leftarrow k+1$
for *each agent* **do**
  if *communication with neighbor devices is successful* **then**
    if *agent is the POI* **then**
      $X_1^k = \text{argmin}_{X_1} G\left(X_1, X_2^{k-1}, X_3^{k-1}, U^{k-1}\right)$
      s.t.: (2.4), (2.5) and (4.3).
    end
    if *agent is the BESS* **then**
      $X_2^k = \text{argmin}_{X_2} G\left(X_1^{k-1}, X_2, X_3^{k-1}, U^{k-1}\right)$
      s.t.: (2.8), (4.4) and (4.5).
    end
    if *agent is the DLC* **then**
      $X_3^k = \text{argmin}_{X_3} G\left(X_1^{k-1}, X_2^{k-1}, X_3, U^{k-1}\right)$
      s.t.: (4.6).
    end
  else
    $X_i^k \leftarrow X_i^{k-1}$
  end
  $Z = [P_{BESS}^{\text{aux}_2}, P_{DLC}^{\text{aux}_3}]$
end
Step 3: Update dual variables
  $U^k = U^{k-1} + (X_1^k - Z^k)$
Step 4: Convergence test
if $\sum \left|X_1^k - Z^k\right| \leq \epsilon$ *and* $\sum \left|U^k - U^{k-1}\right| \leq \epsilon$ **then**
  End algorithm
else
  Return to Step 2
end

4.3 EMS considering the internal network

This model consists of the energy management of the DERs located within the microgrid, the DERs are interconnected by an internal network. Considering the context of a multi-agent system for the microgrid, each DG, DR load/RES, BESS is represented by the respective optimal energy dispatch agent. Each agents is associated with a node, it can interact with neighboring nodes in order to optimize the global operation of the microgrid.

The objective is to decompose the problem, obtaining subproblems for each agent. Therefore, a subproblem per node is solved. Thus, the model (2.9)–(2.15) is distributed, considering that each node is an independent agent. It is observed that the variable $f^{j\to h}$ complicates the decomposition of the problem, because it associates two nodes: j and h. Thus, auxiliary variables $f_j^{j\to h}$ and $f_h^{j\to h}$ are introduced to substitute $f^{j\to h}$ where each auxiliary variable is associated with nodes j and h, respectively. Consequently, constraints (2.13) and (2.15) are modified by (4.17) and (4.18). Note that $f_j^{j\to h}$ must be equal to $f_h^{j\to h}$; hence, constraint (4.19) is required.

$$P_i = \sum_{j\to h\in E_i} d_i^{j\to h} f_i^{j\to h} \qquad \forall\ j\to h\in E_i, \forall\ i\in N \quad (4.17)$$

$$\underline{f}^{j\to h} \le f_i^{j\to h} \le \overline{f}^{j\to h} \qquad \forall\ j\to h\in E_i, \forall\ i\in N \quad (4.18)$$

$$f_j^{j\to h} = f_h^{j\to h} \qquad \forall j\to h\in E \quad (4.19)$$

The reformulated problem is described by (2.9)–(2.12), (2.14), and (4.17)–(4.19). Even if the auxiliary variables have been created, the problem can not still be decomposed, because the constraint (4.19) involves two variables from different nodes. Therefore, to reach the total distribution of the problem, the auxiliary constraint (4.19) will be raised to the objective function by means of the Augmented Lagrangian technique leaving the problem distributed as follows:

$$\min \left\{ \sum_{i\in N} \left[C_i\left(P_i\right) - C_0\left(P_i\right)\right] + \sum_{j\to h\in E_i, i\in N} \left[\lambda^{j\to h}\left(f_j^{j\to h} - f_h^{j\to h}\right) + \rho/2\left(f_j^{j\to h} - f_h^{j\to h}\right)^2\right] \right\} \quad (4.20)$$

Subject to (2.9)–(2.11), (2.14), (4.17), (4.18).

With the problem approach mentioned above, this can already be distributed through ADMM. Firstly, synchronous non-scaling ADMM is used to decompose the problem into subproblems per node in the iteration k as follows:

For node i:

$$\begin{aligned}\min_{P_i, f_i^{j\to h}} \{ & C_i\left(P_i\right) - C_0\left(P_i\right) \\ & + \sum_{j\to h \in E_i, i=j} \left[\lambda^{j\to h,k-1}\left(f_j^{j\to h} - f_h^{j\to h,k-1}\right) + \rho/2\left(f_j^{j\to h} - f_h^{j\to h,k-1}\right)^2\right] \\ & + \sum_{j\to h \in E_i, i=h} \left[\lambda^{j\to h,k-1}\left(f_j^{j\to h,k-1} - f_h^{j\to h}\right) + \rho/2\left(f_j^{j\to h,k-1} - f_h^{j\to h}\right)^2\right]\Bigg\}\end{aligned} \tag{4.21}$$

Subject to (2.9)–(2.11), (2.14), (4.17), (4.18).

For a more straightforward representation, the augmented Lagrangian in (4.20) is expressed as $M(P_i, \lambda^{j\to h}, f_j^{j\to h}, f_h^{j\to h})$. The process for deploying the unscaled synchronous ADMM is given by Algorithm 5, where, at the k-th iteration: $\lambda^{j\to h,k}$, $f_j^{j\to h,k}$, and $f_h^{j\to h,k}$ are considered parameters.

The previous case in Algorithm 5 is valid only if a synchronous communication is taken into account, however the system is vulnerable to problems with the sending of information due to failures or delays in communication between agents. Then, similarly to the asynchronous model of the previous Section 4.3, an unscaled asynchronous ADMM algorithm is performed to EMS considering the internal network. The process for deploying the unscaled synchronous ADMM is given by Algorithm 6.

Rewriting the distributed EMS considering the internal network via unscaled synchronous ADMM into scaled synchronous ADMM, the dual variables are scaled in the

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Algoritmo 5: Unscaled synchronous ADMM for a EMS considering the internal network

---

Step 1: Initialization
$k \leftarrow 0$
$f_i^{j\to h,k} \leftarrow 0,\ \lambda^{j\to h,k} \leftarrow 1,\ \forall\ i \in N, j \to h \in E_i$
Step 2: Subproblem for each node i in N, with $(j \to h) \in E_i$
$k \leftarrow k+1$
for $i \in N$ **do**
  $\{P_i, f_i^{j\to h,k}\} = \operatorname{argmin}_{\{P_i, f_i^{j\to h}\}} M(P_i, \lambda^{j\to h}, [f_j^{j\to h}, f_h^{j\to h,k-1}]_{i=j}, [f_j^{j\to h,k-1}, f_h^{j\to h}]_{i=k})$
end
Step 3: Update dual variables
  $\lambda^{j\to h,k} = \lambda^{j\to h,k-1} + \rho(f_j^{j\to h,k} - f_h^{j\to h,k}), \forall j \to h \in E$
Step 4: Convergence test
if $\sum_{j\to h} |f_j^{j\to h,k} - f_h^{j\to h,k}| \leq \epsilon$ *and* $\sum_{j\to h} |\lambda^{j\to h,k} - \lambda^{j\to h,k-1}| \leq \epsilon$ **then**
  End algorithm
else
  Return to Step 2
end

Algoritmo 6: Unscaled asynchronous ADMM for a EMS considering the internal network

Step 1: Initialization
$k \leftarrow 0$
$f_i^{j\to h,k} \leftarrow 0, \lambda^{j\to h,k} \leftarrow 1,\ \forall\ i \in N, j \to h \in E_i$
Step 2: Subproblem for each node i in N, with $(j \to h) \in E_i$
$k \leftarrow k+1$
for $i \in N$ **do**
    if *communication with neighbor nodes is successful* **then**
        $\{P_i, f_i^{j\to h,k}\} = \operatorname{argmin}_{\{P_i, f_i^{j\to h}\}} M(P_i, \lambda^{j\to h}, [f_j^{j\to h}, f_h^{j\to h,k-1}]_{i=j}, [f_j^{j\to h,k-1}, f_h^{j\to h}]_{i=k})$
    else
        $f_i^{j\to h,k} \leftarrow f_i^{j\to h,k-1}$
    end
end
Step 3: Update dual variables
    $\lambda^{j\to h,k} = \lambda^{j\to h,k-1} + \rho(f_j^{j\to h,k} - f_h^{j\to h,k}), \forall j \to h \in E$
Step 4: Convergence test
if $\sum_{j\to h} |f_j^{j\to h,k} - f_h^{j\to h,k}| \leq \epsilon$ *and* $\sum_{j\to h} |\lambda^{j\to h,k} - \lambda^{j\to h,k-1}| \leq \epsilon$ **then**
    End algorithm
else
    Return to Step 2
end

following way: $u^{j\to h} = \lambda^{j\to h}/\rho, \forall j \to h \in E$. Thus, scaling the dual variable and combining the linear and quadratic terms in the augmented Lagrangian (4.20), (4.22) is obtained:

$$\min\left\{\sum_{i\in N}\left[C_i\left(P_i\right) - C_0\left(P_i\right)\right] + \sum_{j\to h\in E_i}\left[\rho/2\left(f_j^{j\to h} - f_h^{j\to h} + u^{j\to h}\right) - \rho/2\left(u^{j\to h}\right)^2\right]\right\} \tag{4.22}$$

Finally, the scaled augmented Lagrangian (4.22) subject to the constrains (2.9)–(2.11), (2.14), (4.17), (4.18) is decomposed through scaled synchronous ADMM. In the iteration k of the algorithm, the number of subproblems obtained is equal to the number of nodes within the microgrid, being each subproblem obtained per node as follows:

For node i:

Algoritmo 7: Scaled synchronous ADMM for a EMS considering the internal network

Step 1: Initialization
$k \leftarrow 0$
$f_i^{j\to h,k} \leftarrow 0,\ u^{j\to h,k} \leftarrow 1/\rho,\ \forall\ i \in N, j \to h \in E_i$
Step 2:Subproblem for each node i in N, with $(j \to h) \in E_i$
$k \leftarrow k+1$
for $i \in N$ **do**
  $\{P_i, f_i^{j\to h,k}\} = \mathrm{argmin}_{\{P_i, f_i^{j\to h}\}} M(P_i, u^{j\to h}, [f_j^{j\to h}, f_h^{j\to h,k-1}]_{i=j}, [f_j^{j\to h,k-1}, f_h^{j\to h}]_{i=k})$
end
Step 3: Update dual variables
  $u^{j\to h,k} = u^{j\to h,k-1} + (f_j^{j\to h,k} - f_h^{j\to h,k}), \forall j \to h \in E$
Step 4: Convergence test
if $\sum_{j\to h} |f_j^{j\to h,k} - f_h^{j\to h,k}| \leq \epsilon$ *and* $\sum_{j\to h} |u^{j\to h,k} - u^{j\to h,k-1}| \leq \epsilon$ **then**
  End algorithm
else
  Return to Step 2
end

$$\begin{aligned}
&\min_{P_i, f_i^{j\to h}} \{C_i(P_i) - C_0(P_i) \\
&\qquad + \sum_{j\to h \in E_i, i=j} \left[\rho/2\left(f_j^{j\to h} - f_h^{j\to h,k-1} + u^{j\to h,k-1}\right) - \rho/2\left(u^{j\to h,k-1}\right)^2\right] \\
&\qquad\quad + \sum_{j\to h \in E_i, i=h} \left[\rho/2\left(f_j^{j\to h,k-1} - f_h^{j\to h} + u^{j\to h,k-1}\right) - \rho/2\left(u^{j\to h,k-1}\right)^2\right]\Bigg\}
\end{aligned} \tag{4.23}$$

Subject to (2.9)–(2.11), (2.14), (4.17), (4.18).

For a more simplified representation, the augmented Lagrangian in (4.22) is expressed as $N(P_i, u^{j\to h}, f_j^{j\to h}, f_h^{j\to h})$. In the same way as for the unscaled synchronous and asynchronous case, the process for deploying the synchronous and asynchronous scaled ADMM is given by Algorithm 7 and Algorithm 8, respectively. Furthermore, it is considered that at the k-th iteration $u^{j\to h,k}$, $f_j^{j\to h,k}$ and $f_h^{j\to h,k}$ are considered parameters.

4.4 Summary

In this chapter the adaptation of the centralized to distributed EMS mathematical optimization models using a combination of different versions of ADMM algorithm mentioned in Chapter 3 (unscaled ADMM, scaled ADMM, synchronous ADMM and asynchronous ADMM) was presented. The centralized models: EMS based on devices and EMS considering the internal network were formulated in the Section 2.2 and Section

Algoritmo 8: Scaled asynchronous ADMM for a EMS considering the internal network

Step 1: Initialization
$k \leftarrow 0$
$f_i^{j\to h,k} \leftarrow 0,\ u^{j\to h,k} \leftarrow 1/\rho,\ \forall\ i \in N, j \to h \in E_i$
Step 2: Subproblem for each node i in N, with $(j \to h) \in E_i$
$k \leftarrow k+1$
for $i \in N$ **do**
  if *communication with neighbor nodes is successful* **then**
    $\{P_i, f_i^{j\to h,k}\} = \operatorname{argmin}_{\{P_i, f_i^{j\to h}\}} M(P_i, u^{j\to h}, [f_j^{j\to h}, f_h^{j\to h,k-1}]_{i=j}, [f_j^{j\to h,k-1}, f_h^{j\to h}]_{i=k})$
  else
    $f_i^{j\to h,k} \leftarrow f_i^{j\to h,k-1}$
  end
end
Step 3: Update dual variables
  $u^{j\to h,k} = u^{j\to h,k-1} + (f_j^{j\to h,k} - f_h^{j\to h,k}), \forall j \to h \in E$
Step 4: Convergence test
if $\sum_{j\to h} |f_j^{j\to h,k} - f_h^{j\to h,k}| \leq \epsilon$ *and* $\sum_{j\to h} |\lambda^{j\to h,k} - \lambda^{j\to h,k-1}| \leq \epsilon$ **then**
  End algorithm
else
  Return to Step 2
end

2.3, respectively, in a general and simple way in order to appreciate the constrains that complicate the distribution of the problem. In addition, both distributed models were based on a multi-agent system architecture, each agent was associated with a DER, which operates autonomously. The multi-agent system complements the ADMM algorithm in terms of reducing the complexity of the problem by dividing it into smaller problems.

5 Test and Results

5.1 Introduction

In this chapter the simulations and results obtained with the method described in Chapter 3 were presented. The simulations are focused on testing the effectiveness and accuracy of the ADMM algorithms: unscaled ADMM, scaled ADMM, synchronous ADMM and asynchronous ADMM through deterministic and statistical evaluations. The effectiveness of the algorithms was carried out through the analysis and comparison of the results obtained in terms of optimality and convergence time of the study cases. For the simulations performed for the study cases, it was considered two test system: A Smart Home model and a Modified IEEE 15-node distribution radial system, which were based on the centralized programming models proposed in the Chapter 2, and its versions distributed through the ADMM algorithm, presented in Chapter 4.

All algorithms were implemented in AMPL (R. Fourer and D. M. Gay and B. W. Kernighan, 2003), and the solutions to the convex subproblems were obtained using the comercial solver CPLEX (IBM ILOG, 2009), in a server with an Intel(R) Xeon(R) CPU E5-2620, 32 GB RAM and 12 cores.

The rest of the chapter is organized as follows: Section 5.2 presents the study cases, Section 5.3 presents the results of a deterministic analysis for the two study cases, Section 5.3.1 presents the results of a statistical analysis for the two study cases . Finally, Section 5.4 contains a summary of the chapter.

5.2 Study Cases

5.2.1 Case 1: Smart-Home

Nowadays, consumers are increasingly converting their homes into “smart homes". A Smart House consists of a set of systems that automates home installations thanks to technological innovations, for the benefit of its inhabitants.

With the development of new technologies such as smart grids, smart meters, electric vehicles, solar panels, storage systems, the paradigm is changing to not only being energy consumers, the prosumer concept and the term residential electrical management appeared, this last term is one of the main advantages that a smart home can offer. The monitoring system allows monitoring the use of DERs in real time, as well as using historical data to develop future operating strategies.

This case is based in the model proposed in 2.2. It consists of managing the resources of a smart-home, which can operate either grid-connected or isolated. The resources included were one rooftop PV unit, critical and non-critical loads with DLC, a BESS, and a POI with the main grid as shown in Fig. 5.1. The smart home model is flexible, the results obtained in the EMS depending on the configuration and the values assigned to the parameters. For subsequent simulations in order to study the ADMM method and its versions, the value of the parameters considered in the smart-home model are shown in the Table 5.1. Besides, the cost of energy purchased from the DN is $C_p = 1.0\,\text{m.u./kWh}$ (monetary units), the cost of energy sold to the DN is $C_s = 0.5\,\text{m.u./kWh}$, and the cost of load curtailment via DLC is $C_{DLC} = 2.0\,\text{m.u./kWh}$.

For the sake of simplicity, only one time interval is optimized in (2.1)–(2.8), and its duration is $\Delta_t = 1$ h. For all ADMM algorithms, the convergence tolerance is $\epsilon = 1 \cdot 10^{-5}$. For the sensibility analysis, simulations were performed with different values of the penalty parameter ρ : 0.01, 0.1, 0.5, 1, 5, 10, 20, and 100. The asynchronous ADMM versions use a random telecommunication delay generator to simulate communication issues between agents at each iteration of Algorithms.

Table 5.1 – Case 1: Values of the parameters

Smart Home Parameter	Value	Measuring Unit
P_{PV}	5.0	kW
P_d	5.0	kW
E^0_{BESS}	2.5	kWh
$\overline{P}_{DLC}$	5.0	kW
$\overline{P}_s$	20.0	kW
$\overline{P}_{BESS}$	5.0	kW
$\overline{E}_{BESS}$	10	kWh

[Source: made by the author]

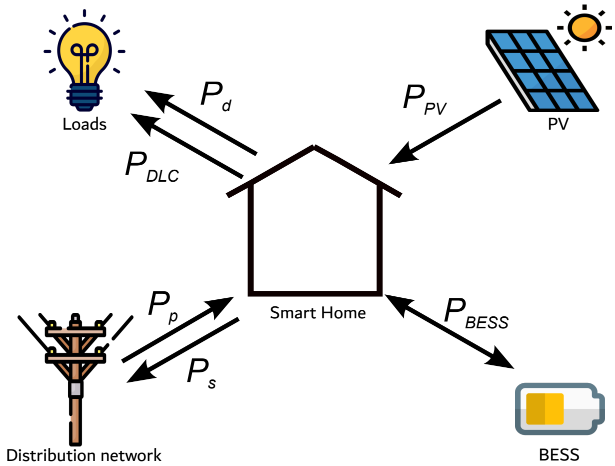


Figure 5.1 – Smart-Home Energy Management System
[Source : made by the author]

5.2.2 Case 2: Modified IEEE 15-node microgrid

A microgrid is a small-scale electrical network that integrates DERs including controlled and variable distributed generation, storage device, controlled and critical loads, and can operate connected or isolated to the distribution network (ZIA; ELBOUCHIKHI; BENBOUZID, 2018) .

This study case is based in the model formulated in subsection 2.3, it includes a modified version of the IEEE 15-node distribution radial system formulated in (ZHENG et al., 2018). The system is shown in Fig. 5.2, it consists of four DGs located at nodes 5 to 8, three BESSs located at nodes 10 to 12, and two prosumers with DR capability located at nodes 14 and 15. The POI is located at node 1. The parameters associated with each DER are detailed in in the Table 5.2. The energy transaction cost at the POI is $C_0 = 5.0\,\text{m.u./kWh}$ and the net demand is 300 kWh. For this study case, the simulations were performed considering only a period of time, with duration of $\Delta_t = 1$ h.

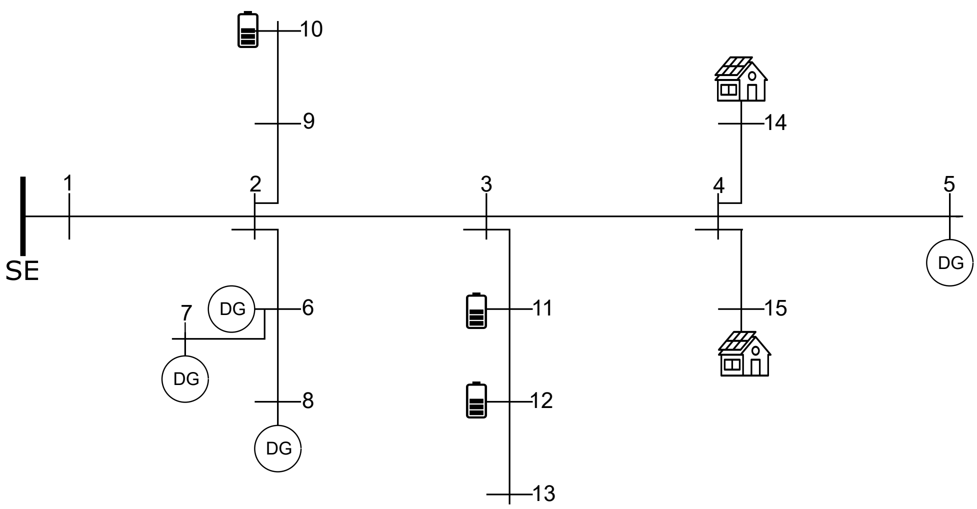


Figure 5.2 – A modified IEEE 15-node distribution radial system [Source: made by the author]

Table 5.2 – Technical Data

DER	Location Node	Parameter			Minimum Power (kW)	Maximum Power (kW)
DG		a_h	b_h	c_h		
	5	0.01	8.5	0	10	100
	6	0.015	8.5	0	10	100
	7	0.01	9	0	5	50
	8	0.015	9	0	5	50
BESS		n_p	n_c	n_{loss}		
	10	0.15	0.01	0.1	-50	50
	11	0.2	0.01	0.12	-30	30
	12	0.3	0.01	0.1	-30	30
DR		n_{inc}	m_{inc}			
	14	0.2	5		-20	20
	15	0.1	10		-20	20

[Source: adapted from (ZHENG et al., 2018)]

The settings for the sensibility analysis, convergence process, and asynchronous communication approach are the same as in the previous case, i.e., the simulations for the sensibility analysis were performed with different values of the penalty parameter ρ : 0.01, 0.1, 0.5, 1, 5, 10, 20, and 100, additionally, the convergence tolerance of $\epsilon = 1 \cdot 10^{-5}$ was set, and, the asynchronous ADMM process was modeled with a random telecommunication delay generator.

5.3 Sensibility Analysis: Deterministic Approach

The study cases were simulated considering deterministic data mentioned in the section 5.2 regarding photovoltaic generation (P_{PV}), demanded power (P_d) , purchase and sale energy costs (C_p, C_s), initial battery state (E^0_{BESS}) for the *Case 1: Smart Home*, and, limits of the power sold or consumed by prosumers ($\underline{P}_{14}$, $\underline{P}_{15}$, $\overline{P}_{14}$, $\overline{P}_{15}$) for the *Case 2: modified IEEE 15-node microgrid*.

Fig 5.3 and 5.4 shows the performance of the four versions of ADMM discussed in the section 3 (i.e., unscaled, scaled, synchronous, and asynchronous) when is applied to the two study cases: *smart-home* and *modified IEEE 15-node microgrid*, respectively, considering the criteria from section 3.

For each version of ADMM, three subplots are shown in each figure from Fig. 5.3 and Fig. 5.4. The first (top) subplot shows the values of the dual residuals $\varepsilon_{\text{dual}}$ at each iteration for different values of ρ. The second (middle) subplot shows the values of the primal residuals $\varepsilon_{\text{primal}}$ at each iteration for different values of ρ. Finally, the third (bottom) subplot shows the values of the objective function at each iteration for different values of ρ. The first two subplots are indicators of the convergence process, whereas the third subplot is an indicator of the optimality because the optimal value obtained as a result of the simulation of the centralized model is depicted by the red dashed line. For all ADMM versions, it is noted that very low (i.e., lower than 0.5) and very large (i.e., larger than 5) values of ρ tend to increase the number of iterations and it may not even reach the optimality, as shown in *Case 1: Smart Home*, $\rho = 100$ does not converge to the optimal value of the objective function.

On the other hand, it is noted that having communication issues (i.e., asynchronous versions of ADMM) increases the time of convergence, but it does not affect the optimality. Finally, it is worth noting that, in both study cases, the scaled and unscaled versions of ADMM behave almost identically for the synchronous and asynchronous versions.

The output values of the variables obtained as a results of the simulations in the two study cases for the centralized and distributed models using the different ρ values are shown in Tables 5.3 – 5.10. It is observed in both cases that although some variables take their critical value: $P_{DLC} = 5kW$ for the *Case 1: Smart Home* in Tables 5.3 – 5.6, and $P_5 = 10kW, P_6 = 10kW, P_7 = 5kW, P_8 = 5kW$ for the *Case 2: modified IEEE 15-node microgrid* in Tables 5.7 – 5.10, the convergence of the ADMM algorithm is not affected. Additionally, in the *Case 1: Smart Home*, Tables 5.7 – 5.10 corroborate the optimality subplots (iii) for all ADMM variations in the Fig 5.3, where for a value of ρ equal to 100, the result do not converge to the optimum.

Table 5.3 – Case 1 - Synchronous Unscaled ADMM: Comparative table of the outputs variables after convergence.

	Boundaries *min*	Boundaries *max*	**Centralized**	**Synchronous Unscaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_p	0	20	2.50	2.50	2.50	2.50	2.50	2.23	1.86	2.50	0.11
P_s	0	20	0	0	0	0	0	0	0	0	0.40
P_{BESS}	-5	5	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-1.12
E_{BESS}	0	10	0	0	0	0	0	0	0	0	1.38
P_{DLC}	0	5	5	5	5	5	5	5	5	5	0.84

Table 5.4 – Case 1 - Synchronous Scaled ADMM: Comparative table of the outputs variables after convergence.

	Boundaries *min*	Boundaries *max*	**Centralized**	**Synchronous Scaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_p	0	20	2.50	2.50	2.50	2.50	2.50	2.23	1.86	2.50	0.11
P_s	0	20	0	0	0	0	0	0	0	0	0.40
P_{BESS}	-5	5	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-1.12
E_{BESS}	0	10	0	0	0	0	0	0	0	0	1.38
P_{DLC}	0	5	5	5	5	5	5	5	5	5	0.84

Table 5.5 – Case 1 - Asynchronous Unscaled ADMM: Comparative table of the outputs variables after convergence.

	Boundaries *min*	*max*	**Centra- lized**	**Asynchronous Unscaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_p	0	20	2.50	2.50	2.50	2.50	2.50	2.50	1.84	2.50	0.23
P_s	0	20	0	0	0	0	0	0	0	0	0.35
P_{BESS}	-5	5	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-1.19
E_{BESS}	0	10	0	0	0	0	0	0	0	0	1.31
P_{DLC}	0	5	5	5	5	5	5	5	5	5	1.06

Table 5.6 – Case 1 - Asynchronous Scaled ADMM: Comparative table of the outputs variables after convergence.

	Boundaries *min*	*max*	**Centra- lized**	**Asynchronous Scaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_p	0	20	2.50	2.50	2.50	2.50	2.50	2.50	1.84	2.50	0.23
P_s	0	20	0	0	0	0	0	0	0	0	0.35
P_{BESS}	-5	5	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-2.50	-1.19
E_{BESS}	0	10	0	0	0	0	0	0	0	0	1.31
P_{DLC}	0	5	5	5	5	5	5	5	5	5	1.06

Table 5.7 – Case 2 - Synchronous Unscaled ADMM: Comparative table of the outputs variables after convergence.

	Boundaries *min*	*max*	**Centra- lized**	**Synchronous Unscaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_1	-300	300	-98.36	-98.36	-98.36	-98.36	-98.36	-98.36	-98.35	-98.35	-98.30
P_2	0	0	0	0	0	0	0	0	0	0	0
P_3	0	0	0	0	0	0	0	0	0	0	0
P_4	0	0	0	0	0	0	0	0	0	0	0
P_5	10	100	10	10	10	10	10	10	10	10	10
P_6	10	100	10	10	10	10	10	10	10	10	10
P_7	5	50	5	5	5	5	5	5	5	5	5
P_8	5	50	5	5	5	5	5	5	5	5	5
P_9	0	0	0	0	0	0	0	0	0	0	0
P_{10}	-50	50	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2
P_{11}	-30	30	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96
P_{12}	-30	30	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45
P_{13}	0	0	0	0	0	0	0	0	0	0	0
P_{14}	-20	20	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
P_{15}	-20	20	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25

Table 5.8 – Case 2 - Asynchronous Scaled ADMM: Comparative table of the outputs variables after convergence.

	Boundaries *min*	*max*	**Centra-lized**	**Asynchronous Unscaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_1	-300	300	-98.36	-98.36	-98.36	-98.36	-98.36	-98.36	-98.35	-98.35	-98.30
P_2	0	0	0	0	0	0	0	0	0	0	0
P_3	0	0	0	0	0	0	0	0	0	0	0
P_4	0	0	0	0	0	0	0	0	0	0	0
P_5	10	100	10	10	10	10	10	10	10	10	10
P_6	10	100	10	10	10	10	10	10	10	10	10
P_7	5	50	5	5	5	5	5	5	5	5	5
P_8	5	50	5	5	5	5	5	5	5	5	5
P_9	0	0	0	0	0	0	0	0	0	0	0
P_{10}	-50	50	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2
P_{11}	-30	30	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96
P_{12}	-30	30	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45
P_{13}	0	0	0	0	0	0	0	0	0	0	0
P_{14}	-20	20	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
P_{15}	-20	20	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25

Table 5.9 – Case 2 - Asynchronous Unscaled ADMM: Comparative table of the outputs variables after convergence

	Boundaries *min*	*max*	**Centra-lized**	**Asynchronous Unscaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_1	-300	300	-98.36	-98.36	-98.36	-98.36	-98.36	-98.33	-98.36	-98.35	-98.35
P_2	0	0	0	0	0	0	0	0	0	0	0
P_3	0	0	0	0	0	0	0	0	0	0	0
P_4	0	0	0	0	0	0	0	0	0	0	0
P_5	10	100	10	10	10	10	10	10	10	10	10
P_6	10	100	10	10	10	10	10	10	10	10	10
P_7	5	50	5	5	5	5	5	5	5	5	5
P_8	5	50	5	5	5	5	5	5	5	5	5
P_9	0	0	0	0	0	0	0	0	0	0	0
P_{10}	-50	50	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2
P_{11}	-30	30	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96
P_{12}	-30	30	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45
P_{13}	0	0	0	0	0	0	0	0	0	0	0
P_{14}	-20	20	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
P_{15}	-20	20	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25

Table 5.10 – Case 2 - Asynchronous Scaled ADMM: Comparative table of the outputs variables after convergence.

	Boundaries *min*	Boundaries *max*	**Centralized**	**Asynchronous Scaled ADMM**							
ρ				0.01	0.1	0.5	1	5	10	20	100
P_1	-300	300	-98.36	-98.36	-98.36	-98.36	-98.36	-98.33	-98.36	-98.35	-98.35
P_2	0	0	0	0	0	0	0	0	0	0	0
P_3	0	0	0	0	0	0	0	0	0	0	0
P_4	0	0	0	0	0	0	0	0	0	0	0
P_5	10	100	10	10	10	10	10	10	10	10	10
P_6	10	100	10	10	10	10	10	10	10	10	10
P_7	5	50	5	5	5	5	5	5	5	5	5
P_8	5	50	5	5	5	5	5	5	5	5	5
P_9	0	0	0	0	0	0	0	0	0	0	0
P_{10}	-50	50	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2
P_{11}	-30	30	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96	19.96
P_{12}	-30	30	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45	23.45
P_{13}	0	0	0	0	0	0	0	0	0	0	0
P_{14}	-20	20	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
P_{15}	-20	20	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25

Detailed information about the performance of each ADMM version for both test cases is shown in Table 5.11 and Table 5.12. The number of iterations is an indicator of the computational speed, whereas column "RE" stands for relative error of the final solution, i.e., "RE" is the perceptual difference between the optimal value of the objective function obtained by the ADMM and the centralized model. In addition, the results in Tables 5.3 – 5.6 are validated in Table 5.11, where it is observed that for the Synchronous case with $\rho = 5, 10, 100$ and for the Asynchronous case with $\rho = 10, 100$ the results do not reach the optimal values.

Table 5.11 – Case 1: Iterations and relative errors for several values of ρ.

	Synchronous Unscaled ADMM		**Synchronous Scaled ADMM**		**Asynchronous Scaled ADMM**		**Asynchronous Scaled ADMM**	
ρ	number of iterations	RE (%)	number of iterations	RE (%)	number of iterations	RE (%)	number of iterations	RE (%)
0.01	192	0	192	0	395	0	395	0
0.1	114	0	114	0	278	0	278	0
0.5	127	0	127	0	315	0	315	0
1	111	0	111	0	268	0	268	0
5	63	11	63	11	431	0	431	0
10	111	26	111	26	176	28	176	28
20	1000*	-	1000*	-	1000*	-	1000*	-
100	59	229	59	229	155	217	155	217

* ADMM reached the maximum number of permitted iterations.

Table 5.12 – Case 2: Iterations and relative errors for several values of ρ.

	Synchronous Unscaled ADMM		**Synchronous Scaled ADMM**		**Asynchronous Scaled ADMM**		**Asynchronous Scaled ADMM**	
ρ	number of iterations	RE (%)	number of iterations	RE (%)	number of iterations	RE (%)	number of iterations	RE (%)
0.01	507	0	507	0	579	0	579	0
0.1	180	0	180	0	190	0	190	0
0.5	216	0	216	0	250	0	250	0
1	400	0	400	0	464	0	464	0
5	1735	0	1735	0	2006	0	2006	0
10	3236	0	3236	0	3863	0	3863	0
20	6008	0	6008	0	7271	0	7271	0
100	24687	0	24687	0	33647	0	33647	0

5.3.1 Sensibility Analysis: Monte Carlo Simulations

An analysis within a deterministic scenario for both case studies is a biased approach for sensibility analysis. Thus, in this subsection, a statistical assessment of the impact of ρ is performed via Monte Carlo simulations. This statistical analysis consists of performing 1000 simulations with uniformly random values of demands (P_d), renewable sources (P_{PV}), energy costs (C_p, C_s) and limits of the power sold or consumed by prosumers ($\underline{P}_{14}$, $\underline{P}_{15}$, $\overline{P}_{14}$, $\overline{P}_{15}$) in order to calculate the median (μ) and standard deviation (σ) for the number of iterations and RE, for each version of ADMM.

The results in Tables 5.13 - 5.16 show that the standard deviation of the number of iterations and RE is lower for values of ρ closer to one and according to ρ moves away from that value, σ increases, and, further, due to the convergence time factor, when $\rho = 100$, 50 Monte Carlo iterations were performed. It is noted that the results of the average values (μ) obtained by the Monte Carlo simulations are similar to those obtained by the deterministic analysis. Moreover, the "RE" values in Tables 5.13 - 5.16 show that high accuracy in terms of optimal value of the objective function is attained when $0.1 \leq \rho \leq 5$, for either the synchronous and asynchronous versions of ADMM. Finally, any noticeable differences between the scaled and unscaled versions of ADMM were not found in this analysis, which is expected, since both are mathematically equivalent (BOYD et al., 2011), and dual variables are not computationally big numbers.

Table 5.13 – Case 1: Median (μ) and standard deviation (σ) of number of iterations, for different values of ρ.

		Synchronous Unscaled ADMM		Synchronous Scaled ADMM		Asynchronous Unscaled ADMM		Asynchronous Scaled ADMM	
	ρ	μ	σ	μ	σ	μ	σ	μ	σ
Number of iterations	0.01	235.44	219.84	235.44	219.84	384.86	217.06	384.86	217.06
	0.1	105.58	69.56	105.58	69.56	236.82	85.47	236.82	85.47
	0.5	88.33	40.68	88.33	40.68	209.52	58.02	209.52	58.02
	1	82.53	30.92	82.53	30.92	200.48	66.18	200.48	66.18
	5	181.83	268.11	181.83	268.11	327.89	270.06	327.89	270.06
	10	379.74	422.29	379.74	422.29	564.90	379.81	564.90	379.81
	20	581.47	451.97	581.47	451.97	737.28	374.75	737.28	374.75
	100	765.17	403.16	765.17	403.16	679.46	410.34	679.46	410.34

Table 5.14 – Case 1: Median (μ) and standard deviation (σ) of RE, for different values of ρ.

		Synchronous Unscaled ADMM		Synchronous Scaled ADMM		Asynchronous Unscaled ADMM		Asynchronous Scaled ADMM	
	ρ	μ	σ	μ	σ	μ	σ	μ	σ
RE	0.01	2.28×10^{-2}	1.60×10^{-1}	2.28×10^{-2}	1.60×10^{-1}	2.24×10^{-2}	1.57×10^{-1}	2.24×10^{-2}	1.57×10^{-1}
	0.1	8.49×10^{-4}	2×10^{-2}	8.49×10^{-4}	2×10^{-2}	1.60×10^{-3}	2.24×10^{-2}	1.60×10^{-3}	2.24×10^{-2}
	0.5	3.70×10^{-3}	4.88×10^{-2}	3.70×10^{-3}	4.88×10^{-2}	1.62×10^{-2}	3.64×10^{-1}	1.62×10^{-2}	3.64×10^{-1}
	1	1.20×10^{-2}	1.14×10^{-1}	1.20×10^{-2}	1.14×10^{-1}	1.11×10^{-2}	1.44×10^{-1}	1.11×10^{-2}	1.44×10^{-1}
	5	8.15×10^{-2}	4.83×10^{-1}	8.15×10^{-2}	4.83×10^{-1}	8.87×10^{-2}	1.56	8.87×10^{-2}	1.56
	10	4.15×10^{-1}	2.31	4.15×10^{-1}	2.31	1.77×10^{-1}	1.60	1.77×10^{-1}	1.60
	20	2.95	4.15×10^{1}	2.95	4.15×10^{1}	1.68	1.59×10^{1}	1.68	1.59×10^{1}
	100	5.73	6.72×10^{1}	5.73	6.72×10^{1}	1.80×10^{1}	3.07×10^{2}	1.80×10^{1}	3.07×10^{2}

Table 5.15 – Case 2: Median (μ) and standard deviation (σ) of number of iterations, for different values of ρ.

		Synchronous Unscaled ADMM		Synchronous Scaled ADMM		Asynchronous Unscaled ADMM		Asynchronous Scaled ADMM	
	ρ	μ	σ	μ	σ	μ	σ	μ	σ
Number of iterations	0.01	492.18	17.51	492.18	17.51	601.81	27.55	601.81	27.55
	0.1	181.15	0.63	181.15	0.63	186.79	7.06	186.79	7.06
	0.5	216.17	2.70	216.17	2.70	247.88	6.66	247.88	6.66
	1	399.01	5.40	399.01	5.40	458.85	12.96	458.85	12.96
	5	1727.6	26.10	1727.6	26.10	2032.4	68.98	2032.4	68.98
	10	3223	51.07	3223	51.07	3843.30	141.74	3843.30	141.74
	20	5981.6	103.50	5981.6	103.50	7277.20	281.61	7277.20	281.61
	100*	24482	516	24482	516	32556	1746.2	32556	1746.2

* For this ρ value, 50 Monte Carlo simulations were carried out.

5.4 Summary

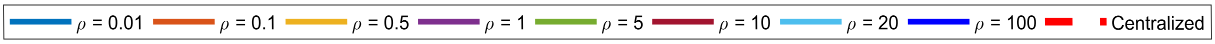
In this chapter, the results of the simulations on two case studies were presented: *Smart Home* and *modified IEEE 15-node microgrid*. The simulations carried out were based on a centralized and distributed model through ADMM in order to test the effectiveness of the ADMM method. Numerical tests with different ρ values applied to the four versions of ADMM (i.e., unscaled, scaled, synchronous, and asynchronous) were performed considering

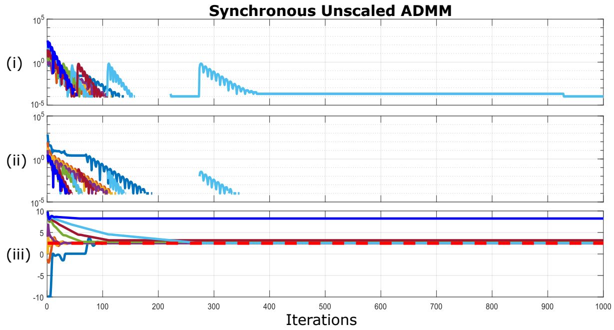
Table 5.16 – Case 2: Median (μ) and standard deviation (σ) of RE, for different values of ρ.

		Synchronous Unscaled ADMM		Synchronous Scaled ADMM		Asynchronous Unscaled ADMM		Asynchronous Scaled ADMM	
	ρ	μ	σ	μ	σ	μ	σ	μ	σ
RE	0.01	1.02×10^{-6}	1.73×10^{-5}	1.02×10^{-6}	1.73×10^{-5}	3.14×10^{-7}	1.35×10^{-6}	3.14×10^{-7}	1.35×10^{-6}
	0.1	2.06×10^{-6}	3.45×10^{-5}	2.06×10^{-6}	3.45×10^{-5}	6.18×10^{-7}	6.93×10^{-6}	6.18×10^{-7}	6.93×10^{-6}
	0.5	2.37×10^{-6}	4.25×10^{-5}	2.37×10^{-6}	4.25×10^{-5}	3.42×10^{-7}	1.20×10^{-6}	3.42×10^{-7}	1.20×10^{-6}
	1	2.38×10^{-6}	4.25×10^{-5}	2.38×10^{-6}	4.25×10^{-5}	4.14×10^{-7}	3.73×10^{-6}	4.14×10^{-7}	3.73×10^{-6}
	5	3.29×10^{-7}	8.30×10^{-6}	3.29×10^{-7}	8.30×10^{-6}	1.10×10^{-3}	3.34×10^{-2}	1.10×10^{-3}	3.34×10^{-2}
	10	1.36×10^{-7}	1.11×10^{-6}	1.36×10^{-7}	1.11×10^{-6}	1.23×10^{-7}	3.67×10^{-7}	1.23×10^{-7}	3.67×10^{-7}
	20	4.31×10^{-7}	8.64×10^{-7}	4.31×10^{-7}	8.64×10^{-7}	2.50×10^{-6}	2.56×10^{-5}	2.50×10^{-6}	2.56×10^{-5}
	100*	1.98×10^{-6}	2.55×10^{-6}	1.98×10^{-6}	2.55×10^{-6}	8.21×10^{-7}	1.17×10^{-6}	8.21×10^{-7}	1.17×10^{-6}

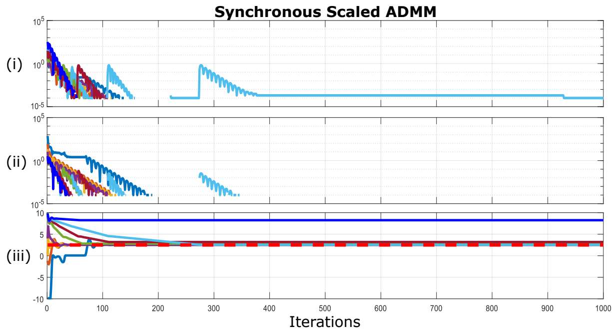
* For this ρ value, 50 Monte Carlo simulations were carried out.

deterministic input parameters of demands, renewable sources and energy costs, and, further, in order to have a more objective view, a statistical analysis is carried out through a Monte Carlo simulations, which consisted of performing 1000 simulations with random values of the same input parameters, followed by the calculation of the median (μ) and standard deviation (σ) of the number of iterations and the relative error.

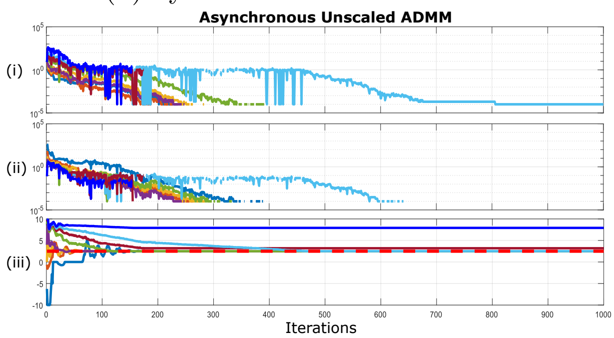




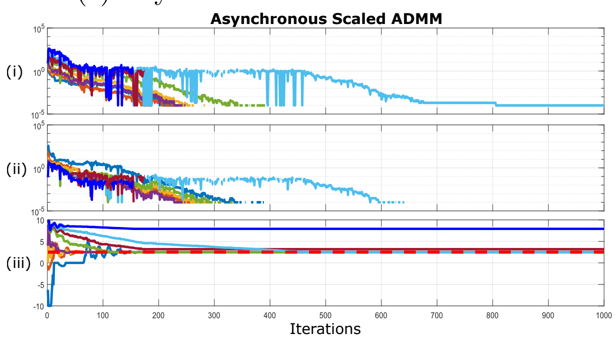
(a) Synchronous Unscaled ADMM



(b) Synchronous Scaled ADMM

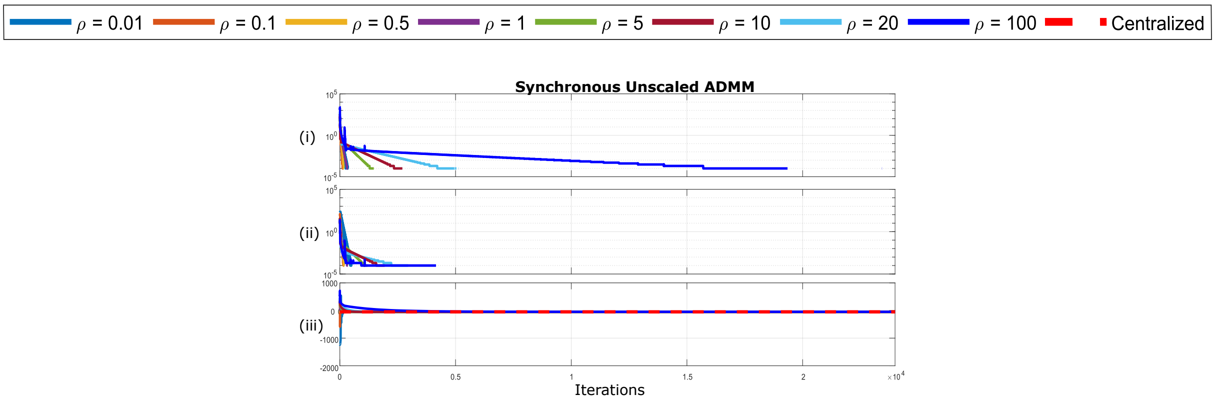


(c) Asynchronous Unscaled ADMM

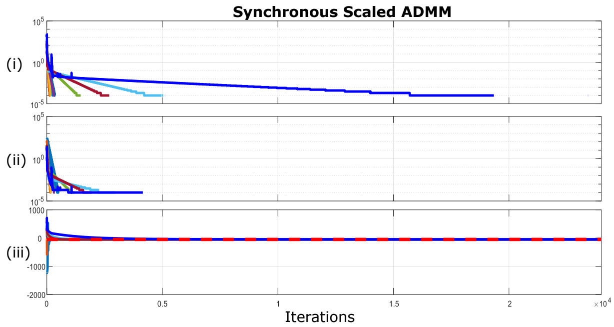


(d) Asynchronous Scaled ADMM

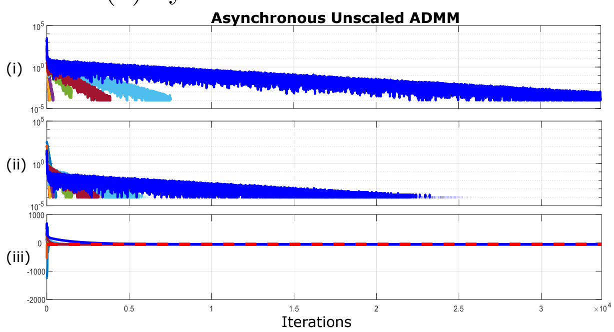
Figure 5.3 – Case 1: Smart Home. Comparison between ADMM versions, deterministic analysis: scaled, unscaled, synchronous, and asynchronous ADMM for different values of ρ. (i) Dual residuals ε_{dual}, (ii) Primal residuals ε_{primal}, (iii) Values of the objective function. [Source: made by the author]



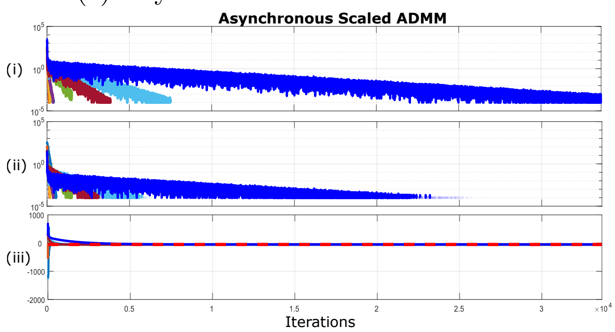
(a) Synchronous Unscaled ADMM



(b) Synchronous Scaled ADMM



(c) Asynchronous Unscaled ADMM



(d) Asynchronous Scaled ADMM

Figure 5.4 – Case 2: Modified IEEE 15-node microgrid. Comparison between ADMM versions, deterministic analysis: scaled, unscaled, synchronous, and asynchronous ADMM for different values of ρ. (i) Dual residuals ε_{dual}, (ii) Primal residuals ε_{primal}, (iii) Values of the objective function. [Source: made by the author]

6 Conclusions

6.1 Conclusions

In this work, two energy management systems (EMS) for microgrids were formulated as convex optimization problems. The first case considers an EMS based on devices without the internal network. The second case considers an EMS with a basic network flow. Both centralized models were distributed via the alternating direction method of multipliers (ADMM) and its versions: unscaled, scaled, synchronous, and asynchronous. For validation, two study cases were used: a *smart-home* and a *modified IEEE 15-node microgrid*. First, a deterministic sensibility analysis was performed, considering different values of ρ and different versions of the ADMM for a single instance of both study cases. The convergence process and optimality were contrasted in this deterministic analysis, which makes it possible to visualize the performance of each ADMM algorithm independently, as functions of the number of iterations. Then, to guarantee an unbiased assessment, a Monte Carlo analysis was carried out by simulating 1000 uniformly random instances of both study cases. Results show that all versions of the ADMM algorithm behave statistically better in terms of optimality and convergence whenever values of $\rho = 1$ are used; a bad choice of ρ can lead to non-optimality and delay convergence. We can verify the robustness of the ADMM method that despite communication problems in the exchange of information between agents or due to a heterogeneous nature of the system, the optimality was not affected, but the convergence may be slower. Furthermore, although the fact that some variables reached their critical value for the different values of ρ tested, the ADMM algorithm converged to the global optimum.

6.2 Future Works

1. Considering a dynamic penalty parameter ρ in the iterative process that is inherent of the ADMM algorithm, which can be adjusted in order to improve the efficiency of the algorithm in terms of solution quality and convergence time.

2. Deploying in a day-ahead framework, using a multi-period version of the algorithm ADMM (GUPTA et al., 2018), for both EMS formulations in microgrids: EMS based on devices and EMS considering the internal network.

3. The scope of the ADMM can be applied to an improvement of the EMS considering the internal network model considering voltage magnitude in buses, active power losses, reactive flow and three-phase electrical network.

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