Distributed Stochastic Economic Dispatch for Smart Grids

A Model Predictive Control Approach

Miguel Andrés Velásquez Motta

Supervisors: Prof. Nicanor Quijano
Prof. Ángela Cadena
Prof. Mohammad Shahidehpour

Committee members: Prof. Alain Gauthier
Prof. Luis Gallego

School of Engineering
Universidad de los Andes

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To my beloved mom and dad, my brother, my family, and my dear love. To all of you, for being the mainstay in all that I am. To the memory of my always present uncle Fabio.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

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Abstract

Power systems have experienced several changes since smart grids and renewable resources increased their penetration. Traditionally, power systems operation has been addressed with unit commitment and economic dispatch problems that rely on a centralized operator. These operation methods are usually performed on a day-ahead basis, i.e., every 24 hours. As a result of volatility in renewable resources and demand, it is better to shorten the operation period, e.g., every hour. Centralized methods might not be feasible for solving short-term economic dispatch, especially in systems with several agents. Thereby, the research questions this thesis are what method can be used for solving short-term economic dispatch in the presence of smart grid elements? Second, what models can be designed in order to optimally dispatch power plants and operate different agents in a smart grid environment? Third, how uncertainty can be considered in such models without increasing dimensionality and keeping tractability? Fourth, what is the best way to operate power systems with smart grid elements? In order to solve all these questions, we deeply analyzed economic dispatch methods and smart grid elements. Next, we proposed two distributed economic dispatch methods that are feasible for hourly and ultra-short term periods. In addition, we integrated stochastic programming through a data-driven scenario generation in order to include randomness of power system variables. Finally, a hierarchical operation of hourly and ultra-short term was proposed to enhance operation performance. The results obtained in this thesis show that proposed methods answer our research questions and serve as a basis for operating power systems more efficiently. Under uncertainty framework, it is better to use stochastic approaches rather than deterministic ones. For using stochastic approaches, it is necessary to pass from centralized controllers to distributed architectures as it has been proposed in this work. In addition, it was confirmed that model predictive control is an appropriate method for solving the economic dispatch problem under uncertainty and to keep a better tracking of the system variables.

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Nomenclature

General notations

$\boldsymbol{y}$	column vectors are denoted by bold style
y	column vectors are denoted by non-bold style
m	total amount of generators
n_r	amount of renewable generators
$\mathbb{1}_m$	column vector with m unitary entries
ϵ	positive value very close to zero
$\lvert \cdot \rvert$	cardinality of a set
k	sampling time discretized by Δt
$\tilde{k}$	sampling time discretized by $\tilde{\Delta} t$, where $\tilde{\Delta} t << \Delta t$
$\check{k}$	sampling time discretized by $\check{\Delta} t$, where $\check{\Delta} t \to 0$

Sets

$\mathbb{R}$	real numbers
$\mathbb{R}_{\geq 0}$	non-negative real numbers
$\mathbb{Z}_{\geq 0}$	non-negative integers
$\mathcal{B}$	energy storage systems (ESS)
$\mathcal{C}$	conventional generators
$\mathcal{E}$	communication links

$\mathcal{M}$	renewable energy-based generators
$\mathcal{N}$	all generators
$\mathcal{N}_v$	neighbors of generator $v \in \mathcal{N}$
$\mathcal{S}$	scenarios
$\mathcal{U}$	renewable energy-based generators with ESS

Discrete time control

$J(\boldsymbol{P})$	cost function
$\boldsymbol{P}$	vector of control inputs $\boldsymbol{P} \in \mathbb{R}^m$
$\boldsymbol{P}^{\min}$	minimum admissible values for $\boldsymbol{P}$, $\boldsymbol{P}^{\min} \in \mathbb{R}^m$
$\boldsymbol{P}^{\max}$	maximum admissible values for $\boldsymbol{P}$, $\boldsymbol{P}^{\max} \in \mathbb{R}^m$
Q	power system load, $Q \in \mathbb{R}_{\geq 0}$
$\Delta\boldsymbol{P}$	slew rate of control inputs, $\Delta\boldsymbol{P} \in \mathbb{R}^m$
$\Delta\boldsymbol{P}^{\min}$	minimum slew rate, $\Delta\boldsymbol{P}^{\min} \in \mathbb{R}^m$
$\Delta\boldsymbol{P}^{\max}$	maximum slew rate, $\Delta\boldsymbol{P}^{\max} \in \mathbb{R}^m$
$\boldsymbol{P}_{k+j\|k}$	prediction made at time k of the vector $\boldsymbol{P}$ for discrete time $k+j$, $\boldsymbol{P}_{k+j\|k} \in \mathbb{R}^m$
$Q_{k+j\|k}$	prediction made at time k of the load Q for discrete time $k+j$, $Q_{k+j\|k} \in \mathbb{R}_{\geq 0}$
$\hat{\boldsymbol{P}}$	control input sequence for a fixed-time forecast period
$\hat{Q}$	forecasted load sequence along H_p
H_p	prediction horizon
w_{vi}	weight of the link between nodes i and v
$\tilde{H}_p$	prediction horizon for ultra-short term dispatch
$\xi_{v,\check{k}}$	auxiliar variable of generator v for the average consensus algorithm at discrete time $\check{k}$

Economic dispatch

π_{k+j}	price of energy at instant $k+j$
$\psi^c_{\ell,k+j}$	local Lagrange multipliers of generator ℓ at instant $k+j$ for $c=1,\dots,4$
$\boldsymbol{\lambda}_k$	vector of Lagrange multipliers at instant k, $\boldsymbol{\lambda}_k \in \mathbb{R}^{H_p+1}$
λ_{k+j}	Lagrange multiplier at instant $k+j$
$P_{\ell,k}$	power produced by generator ℓ at instant k
$P_\ell^{\min}$	minimum power limit of generator ℓ
$P_\ell^{\max}$	maximum power limit of generator ℓ
$\Delta P_{\ell,k}$	slew rate of generator ℓ at instant k
$\Delta P_\ell^{\min}$	minimum slew rate of generator ℓ
$\Delta P_\ell^{\max}$	maximum slew rate of generator ℓ
a_ℓ	quadratic cost component of generator ℓ
b_ℓ	linear cost component of generator ℓ
a_v	quadratic cost component of generator v
b_v	linear cost component of generator v
T	Operation horizon
$C_\ell(P_{\ell,k})$	production cost of generator ℓ
Q_k	load of the system at instant k
$P_{v,k+j\|k}$	prediction of power produced by generator v for discrete time $k+j$ at instant k
$P^{\min}_{v,k+j\|k}$	prediction of minimum power limit of generator v for discrete time $k+j$ at instant k
$P^{\max}_{v,k+j\|k}$	prediction of maximum power limit of generator v for discrete time $k+j$ at instant k
$\Delta P_{v,k+j\|k}$	slew rate prediction of generator v for discrete time $k+j$ at instant k

$\Delta P^{\min}_{v,k+j|k}$ minimum slew rate prediction of generator v for discrete time $k+j$ at instant k

$\Delta P^{\max}_{v,k+j|k}$ maximum slew rate prediction of generator v for discrete time $k+j$ at instant k

$C_v(P_{v,k+j|k})$ production cost prediction of generator v for discrete time $k+j$ at instant k

$SOC_{b,k+j|k}$ prediction of state of charge of battery b for discrete time $k+j$ at instant k

$SOC^{\min}_{b}$ minimum state of charge of battery b

$SOC^{\max}_{b}$ maximum state of charge of battery b

P^{cap}_{b} rated capacity of battery b

$\psi^{h}_{v,k+j}$ local Lagrange multipliers of generator v at instant $k+j$ for $h = 1, \ldots, 4$

$\Psi_{\ell,k+j}$ auxiliary variable for achieving balance at instant $k+j$

$\hat{P}^{\min}_{r,k+j}$ prediction of minimum generation potential of renewable generator r

$\hat{P}^{\max}_{r,k+j}$ prediction of minimum generation potential of renewable generator r

$\tilde{D}_{k+j}$ demand for renewable generators at instant $k+j$

$P^{r}_{u,k+j|k}$ prediction of renewable power of generator u for discrete time $k+j$ at instant k

$P^{b}_{u,k+j|k}$ prediction of battery power of generator u for discrete time $k+j$ at instant k

$\hat{P}^{r,\min}_{u,k+j}$ prediction of minimum generation potential of renewable generator u

$\hat{P}^{r,\max}_{u,k+j}$ prediction of maximum generation potential of renewable generator u

$\Delta P^{r}_{u,k+j|k}$ slew rate prediction of renewable generator u for discrete time $k+j$ at instant k

$\Delta P^{r,\min}_{u,k+j}$ minimum slew rate prediction of renewable generator u for discrete time $k+j$

$\Delta P^{r,\max}_{u,k+j}$ maximum slew rate prediction of renewable generator u for discrete time $k+j$

$P^{b,\min}_{u,k+j}$	maximum charging capacity of battery in generator u for discrete time $k+j$
$P^{b,\max}_{u,k+j}$	maximum discharging capacity of battery in generator u for discrete time $k+j$
$SOC_{u,k+j\|k}$	prediction of state of charge of generator u for discrete time $k+j$ at instant k
$SOC^{\min}_u$	minimum state of charge of battery in generator u
$SOC^{\max}_u$	maximum state of charge of battery in generator u
$\boldsymbol{\pi}_{\tilde{k}}$	vector of price of energy at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\boldsymbol{\Psi}_{\ell,\tilde{k}}$	auxiliary variables at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\tilde{\boldsymbol{q}}_{\ell,\tilde{k}}$	hypothetical generation at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\boldsymbol{E}_{\tilde{k}}$	total power from batteries at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\boldsymbol{P}_{v,\tilde{k}}$	power trajectory of resource v at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\tilde{\boldsymbol{D}}_{\tilde{k}}$	load for renewables at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\tilde{\boldsymbol{R}}_{\tilde{k}}$	total power from renewables at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\hat{\boldsymbol{D}}_{\tilde{k}}$	system load at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\boldsymbol{\Delta}^{R}_{\tilde{k}}$	auxiliary variable of renewables at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\boldsymbol{r}^{\text{up}}_{\ell,\tilde{k}}$	flags of ramp-up active constraint at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\boldsymbol{r}^{\text{down}}_{\ell,\tilde{k}}$	flags of ramp-down active constraint at iteration $\tilde{k}$, $\in \mathbb{R}^{Hp+1}$
$\boldsymbol{q}^{\text{lim}}_{\ell,\tilde{k}}$	operational generation limit due to ramp-up at iteration $\tilde{k} \in \mathbb{R}^{Hp+1}$
$\boldsymbol{q}^{\text{dlim}}_{\ell,\tilde{k}}$	operational generation limit due to ramp-down at iteration $\tilde{k} \in \mathbb{R}^{Hp+1}$
q^{ideal}	auxiliary hypothetical generation without constraints
$P^{*}_{\ell,k-1}$	optimal initial condition of generator ℓ
$\mu_{\tilde{k}}$	Lagrange multiplier of energy balance at discrete time $\tilde{k}$
α	update weight for the dual decomposition algorithm

$\xi_{\ell,\check{k}}$	auxiliar variable of generator ℓ for the average consensus algorithm at discrete time $\check{k}$
$\boldsymbol{z}_\ell$	vector of auxiliar variables for the dual decomposition algorithm, $\boldsymbol{z}_\ell \in \mathbb{R}^{H_p+1}$
$\boldsymbol{Z}_{\tilde{k}}$	matrix of auxiliar variables of generators, at instant $\tilde{k}$, $\boldsymbol{Z}_{\tilde{k}} \in \mathbb{R}^{H_p+1\times n}$
$\boldsymbol{q}_k$	vector of the system load prediction at instant k, $\boldsymbol{q}_k \in \mathbb{R}^{H_p+1}$
$\boldsymbol{\varepsilon}_{\tilde{k}}$	vector of auxiliar variables for calculating $\boldsymbol{\lambda}_k$, at instant $\tilde{k}$, $\boldsymbol{\varepsilon}_{\tilde{k}} \in \mathbb{R}^{H_p+1}$
$\boldsymbol{\xi}_{\ell,\check{k}}$	vector of auxiliar variables for the average consensus algorithm of generator ℓ, at instant $\check{k}$

Stochastic programming

$\boldsymbol{x}$	vector of scenario values
$\boldsymbol{p}$	vector of scenario probabilities
w_i	importance weight of statistical property i
f_i	function of statistical property i
χ_i	statistical property i of historical data
N	quantity of scenarios per stage
p_l	probability of value x_l
p_s	probability of scenario s
λ^s_{k+j}	Lagrange multiplier at instant $k+j$ in scenario s
$\psi^{c,s}_{\ell,k+j}$	local Lagrange multipliers of generator ℓ at instant $k+j$ for $c = 1,\ldots,4$
μ_M, σ_M	Montecarlo mean and standard deviation
μ_d, σ_d	mean and standard deviation of historical data
μ_c, σ_c	mean and standard deviation of costs
μ_b, σ_b	mean and standard deviation of benefits
π^s_{k+j}	price of energy at instant $k+j$ in scenario s

$P^{s}_{v,k+j|k}$ prediction of power produced by generator v for discrete time $k+j$ at instant k in scenario s

$P^{\text{min,s}}_{v,k+j|k}$ prediction of minimum power limit of generator v for discrete time $k+j$ at instant k in scenario s

$P^{\text{max,s}}_{v,k+j|k}$ prediction of maximum power limit of generator v for discrete time $k+j$ at instant k in scenario s

$\Delta P^{s}_{v,k+j|k}$ slew rate prediction of generator v for discrete time $k+j$ at instant k in scenario s

$SOC^{s}_{b,k+j|k}$ prediction of state of charge of battery b for discrete time $k+j$ at instant k in scenario s

$\Psi^{s}_{\ell,k+j}$ auxiliary variable for achieving balance at instant $k+j$ in scenario s

$\hat{P}^{\text{min,s}}_{r,k+j}$ prediction of minimum generation potential of renewable generator r in scenario s

$\hat{P}^{\text{max,s}}_{r,k+j}$ prediction of minimum generation potential of renewable generator r in scenario s

$\tilde{D}^{s}_{k+j}$ demand for renewable generators at instant $k+j$ in scenario s

$P^{r,s}_{u,k+j|k}$ prediction of renewable power of generator u for discrete time $k+j$ at instant k in scenario s

$P^{b,s}_{u,k+j|k}$ prediction of battery power of generator u for discrete time $k+j$ at instant k in scenario s

$\hat{P}^{r,\min,s}_{u,k+j}$ prediction of minimum generation potential of renewable generator u in scenario s

$\hat{P}^{r,\max,s}_{u,k+j}$ prediction of maximum generation potential of renewable generator u in scenario s

$\Delta P^{r,s}_{u,k+j|k}$ slew rate prediction of renewable generator u for discrete time $k+j$ at instant k in scenario s

$SOC^{s}_{u,k+j|k}$ prediction of state of charge of generator u for discrete time $k+j$ at instant k in scenario s

Acronyms / Abbreviations

CDF	Cumulative Distribution Function
CMPC	Centralized Model Predictive Control
DDMPC	Dual Distributed Model Predictive Control
DMP	Distribution Matching Problem
DMPC	Distributed Model Predictive Control
ECDF	Empirical Cumulative Distribution Function
ESS	Energy Storage System
GLF	Generalized Logistic Function
MMP	Moment Matching Problem
MPC	Model Predictive Control
PV	Solar Photovoltaic
TC	Termination Constraint
UC	Unit Commitment

Chapter 1

General introduction

1.1 Motivation

The electric power system is one of the most important areas of analysis worldwide as it impacts economics, development, environment, and in general it is transversal to society structures. Traditionally, the power system has been composed by large-scale power plants, transmission network, distribution grid, and customers that receive energy from generators. Electricity has several features that makes it a special commodity [6]. First, electricity is conduction bounded, i.e., it is very complex to deliver an electron to very large distances. Second, electricity is fungible, and third, it is not storable (at least from an economic point of view). This last characteristics implies that generation and demand must be balanced at any time. In order to address energy balance, several authors have successfully worked and proposed different methods for operating power systems [60, 56, 5, 57, 28]. However, with the great changes that power systems have experienced in the last two decades, the operation problem has gathered new attention.

For long time, power systems have been composed by large-scale power plants that primarily used coal, fuel, and hydro resources for generating electricity. These plants could be located far away from load centers, thereby it has been necessary to use a large infrastructure for delivering produced energy to final users. Nevertheless, electricity systems have experienced several changes, which are the result of technology breakthroughs and environmental concerns. For instance, solar radiation usage has growth recently as a consequence of technology improvements although its potential use was published several decades ago [64]. In the last years, new elements have appeared and some others have changed their functionality. First, renewable resources such as wind speed, solar radiation, biomass, water stream, among others, have been used lately for generating electricity through feasible conversion systems. Second, energy can be stored by implementing different systems like Lithium-ion batteries, flywheels, hydrogen cells, and others. Energy storage systems can be found as well in electric mobility. Third, users are now more active and they can take decisions by considering the system information, e.g., energy price. Finally, advances in electronics have enable as well the use of better control and communication architectures, and design of more complex devices with a kind of intelligence inside. Altogether these new elements compose the concept of smart grid.

On one hand, The smart grid concept is a new trend in power systems that comprehends and integrates economics, policy and regulation, control and automation, communication systems, grid infrastructure, and technical criteria. This new concept enables a more efficient supply of energy through the active interaction between demand, offer, and the system operator. In this way, the changes mentioned before play a key role. For instance, demand response programs help to reduce the system peak load by using smart meters and economic incentives. As a result, there is a price reduction and a higher margin of operation. In terms of challenges, some renewable resources (wind speed and solar radiation) along with energy demand and other components of the system, have a stochastic behavior. Uncertainty may lead to operational problems since current dispatch models do not take into account the unpredictable behavior of demand and offer.

On the other hand, economic dispatch and energy management systems have been proposed to be solved by a centralized controller. Benefits of central architectures comprehend simplicity of optimization problems for maximizing social benefits and ease of maintenance. As challenges, centralized approaches can be highly unstable, with low scalability, with a very demanding communication network (especially for wide geographical areas), and its dimensionality can grow very high. In turn, distributed approaches are more scalable, their dimensionality grows slower, more stable (its behavior does not rely on a single node). However, their main inconvenience is the complexity of low level operations and the possibility to reach global benefits in the presence of coupled constraints.

The economic dispatch problem now must be solved by taking into account uncertainty from different resources and load [52]. However, addressing randomness by implementing a centralized approach may lead to tractability issues and *curse of dimensionality* [31] when solving for short-term periods (e.g., one hour). Indeed, the dynamic economic dispatch of a large-scale power system may not be feasible in polynomial time [31]. In consequence, it is preferred to use distributed methods where dimensionality grows slower than centralized architectures. This feature is even more crucial when combining stochastic programming with dynamic energy management systems as the number of decision variables increase exponentially. In this doctoral research, we propose to use model predictive control strategies that allow us to consider the dynamic behavior of the power system while controlling optimally the output of power plants with information feedback.

This doctoral thesis provides three different strategies for solving the economic dispatch problem of power systems in a distributed manner and considering uncertainty. First, we propose an economic dispatch based on dual decomposition and average consensus that is feasible for hourly periods and shorter terms in some cases. Second, we propose another economic dispatch that relies on novel algorithms for complying with ramp-rate limits and that is feasible for ultra-short term periods (e.g., 5 minutes). Uncertainty of both approaches is addressed by using a data-driven scenario generation and applying it to MPC stochastic programming. Finally, hourly and ultra-short term dispatches are combined through a master-slave configuration that accounts for avoiding sub-optimality in real-time (5 minutes) applications.

1.2 Research questions

The main purpose of this doctoral thesis is to design distributed optimization problems that accounts for the economic dispatch in power systems by using model predictive control and stochastic programming. The following key research questions motivate and drive the focus of this thesis:

1. What implications and changes provoke the elements of smart grids in power systems operation?
2. What kind of method is more suitable to deal with volatility and dynamics in power systems operation?
3. How can be modeled and solved an economic dispatch problem that maximizes global benefit, that is feasible for hourly periods, and that considers uncertainty?
4. What model can be used for shortening the computational burden of economic dispatch problems under uncertainty for real time applications?
5. How uncertainty can be included in the operation of smart grids and large-scale power grids?

6. How efficiency and performance of power systems can be enhanced in a feasible computational time?

The aforementioned questions are developed throughout this document. The first two questions allow us to create and analyze the context where the solution can be deployed. The next questions represent the main contributions of this thesis.

1.3 Thesis outline and main contributions

This thesis is divided into four parts that are organized as chapters. The document is structured as follows:

Chapter 2: This chapter contains the first approximation to the dynamic economic dispatch problem by using model predictive control. Here, the general concept of MPC is described and characterized. This concept is applied to the economic dispatch in order to verify its advantages and main features to be considered. As a result, we observed how MPC is appropriate for controlling power systems operation by considering and tracking its changes. Thereby, this chapter gives insights about the first two research questions. The main contribution on this topic is MPc verification as an appropriate alternative to deal with the economic dispatch problem. This chapter is associated to the following publication:

- M. A. Velasquez, N. Quijano and A. I. Cadena, "Model Predictive Control Applied to the Dynamic Economic Dispatch Problem," in IEEE Latin America Transactions, vol. 15, no. 4, pp. 656-662, April 2017.

Chapter 3: This chapter addresses the third question regarding the hourly economic dispatch problem. Usually, this kind of optimization problem has been solved from a centralized perspective. However, with the penetration of renewable resources and high volatility, more operation scenarios must be considered. When taking into account more scenarios in a dynamic framework, dimensionality of the problem increases and so it does the computational burden. A distributed economic dispatch that emulates the centralized approach is provided in this chapter, and is the main contribution on this matter. The proposed method uses dual-decomposition and average consensus algorithm in order to comply with the balance coupled constraint while maximizing social benefits. This chapter is supported by the following publication:

- M. A. Velasquez, J. Barreiro-Gomez, N. Quijano, A. I. Cadena, and M. Shahidehpour, "Distributed Model Predictive Control for Economic Dispatch of Power

Systems With High Penetration of Renewable Energy Resources," submitted to IEEE Transactions on Sustainable Energy.

Chapter 4: This chapter looks for a distributed method that decreases the computational burden of the proposed hourly dispatch in order to solve it for the ultra-short term, i.e., 5 minutes. Since hourly dispatch approach maximizes the social benefit, it complies with a coupled constraint of energy balance. That approach converges in average in 203 iterations for the analyzed case study. Even though the distributed iterative hourly dispatch is feasible for short-term applications and hourly periods, it might not be feasible for ultra-short term when considering several scenarios and a large prediction horizon. Thereby, a novel method that is feasible for the ultra-short term is proposed in this chapter, solving the fourth research question. The proposed approach relies on several algorithms that ensures feasibility of solutions by considering ramp-rate limitations. In addition, this method does not include an explicit balance constraint but complies with it implicitly by finding an optimal energy price. Although this method converges very fast to an optimal solution (8 iterations in average), the trade-off is that it no longer maximizes the social benefit but the agents' profit. In addition, this chapter provides distributed formulations for different elements of smart grids. Such formulations are valid for both the hourly approach proposed in chapter 3 and ultra-short term dispatch. The main contributions in this chapter are the ultra-short term distributed dispatch that complies with ramp-rate limits, and distributed formulation for smart grid elements, while keeping energy balance. The following publication supports this chapter:

- M. A. Velasquez, J. Barreiro-Gomez, N. Quijano, A. I. Cadena, and M. Shahidehpour, "Intra-Hour Microgrid Economic Dispatch Based on Model Predictive Control," submitted to IEEE Transactions on Smart Grid.

Chapter 5: This chapter presents the method used for including uncertainty in the distributed MPC formulations provided in chapter 3 and chapter 4. The main reason for developing distributed approaches instead of centralized ones is that dimensionality increases in the last when dealing with uncertainty. Since behavior of smart grid elements is highly random, operation of new power systems must be solved from a stochastic framework. Traditionally, uncertainty has been addressed in optimization problems through chance constraints, robust optimization, and stochastic programming. The first two approaches are not applicable to the formulations presented in this thesis as those problems are always feasible. Thereby, stochastic programming is used through a data-driven scenario generation algorithm. This chapter solves the fifth research question. Moreover, the last research question regarding to power systems performance, is addressed here by proposing a master-slave configuration between hourly and ultra-short term dispatches. To the best of our knowledge, there are no researches on MPC economic dispatch that explicitly includes uncertainty. The main contributions on this matter are: i) an MPC-based economic dispatch that considers uncertainty through stochastic programming and ii) a hierarchical configuration that enhances power system operation even for the ultra-short term. This chapter relies on the following publications and presentations:

- M. A. Velasquez, N. Quijano, A. I. Cadena, and M. Shahidehpour, "Distributed Stochastic Economic Dispatch via Model Predictive Control and Data-Driven Scenario Generation," to be submitted to IEEE Transactions.
- Some contents of this thesis were presented at the conference "Clean Energy for the World's Electricity Grids", United Scientific Group, Geneva, Switzerland, November 2017.

Chapter 6: This final chapter draws the concluding remarks of this doctoral thesis, its contributions, and proposes some questions that still remain open and can be analyzed in future work.

Chapter 2

Model Predictive Control Applied to the Dynamic Economic Dispatch Problem

Power system operation has been a very complex and interesting problem, and currently has gathered more attention because of new elements in the network. New elements such as renewable sources, demand response, electric vehicles, and energy storage systems, are crucial because of their stochastic behavior. Stochastic variables present new challenges for the system operator, who must prevent future changes in the network status by taking efficient decisions with available information. In this chapter we show that MPC might be appropriate to solve the economic dispatch problem when feasible future events are considered. A case study is solved from different perspectives of the system operator, which is able to consider or neglect future events. Results show that MPC efficiently solves the economic dispatch problem when considering future events and ramp rate constraints.

2.1 Introduction

Several generators provide the energy required by customers, and comprises both renewable and non-renewable resources (e.g., hydropower and coal). In the system operation, the operator must choose which generators will fit demand by taking into account features such as production costs and resources availability. In order to find an appropriate configuration of power plants, it is necessary to solve an optimization problem with economic or technical criteria, or a combination of both. In most of the cases, the operator uses operational costs as the objective function and considers constraints of machines and resources. Operational costs are directly related to the cost of generation resources such as price of coal or opportunity cost of water.

Some mechanisms allow the operator to efficiently set energy output for each generator. Commonly, these mechanisms are known as unit commitment, economic dispatch, and balance. On one hand, the UC provides On/Off status of power plants for a specific time interval, and it is generally executed once a day for the next 24 hours. On the other hand, the economic dispatch specifies power delivery by each generator turned on in the UC. Since the information used in the UC can experience some deviations, economic dispatch must be solved for shorter periods, e.g., one hour. Because of this requirement, economic dispatch does not include all the constraints and complexity of UC, which is heavier in computational terms. Finally, the balance stage is in charge of covering possible deviations within the economic dispatch period. In the balance stage, it is possible to take different actions according to the deviation magnitude and response time. For instance, large deviations may require re-dispatching, while small deviations can be corrected with primary control of machines.

Towards finding an optimal operation point, the operator must consider possible scenarios of future events because of technical constraints and uncertain variables. Technical constraints are both single interval (i.e., depend on present information) and inter-temporal (i.e., depend on past or future information). On one hand, in the single interval constraints can be found the following: capacity limits of generators, demand of energy, security constraints of the network, among others. On the other hand, inter-temporal constraints comprise ramp rate limits, On/Off minimum time, energy limited resources (e.g., batteries), and so forth. Because of the constraints nature, it is necessary to use dynamic optimization methods such as dynamic programming, optimal control, and model predictive control, which is the focus of this research. In addition, uncertain variables (such as wind speed, solar radiation, and demand behavior) bring about new challenges for the system operator. Case in point, deviation of renewable resources implies that traditional power plants must increase or decrease their output in order to maintain the balance between demand and generation. With good forecasting models and with a scheme that considers stochastic scenarios, the system operator would be able to predict whether it is appropriate to turn on/off a thermal plant such that balancing costs are minimized [47].

Operational problems may arise as a result of the unpredictable behavior of system variables since current dispatch models do not include this uncertainty. At present, the unpredictable behavior of renewable resources and the uncertainty of demand have gathered special attention to be included in economic dispatch models. Morales et al. in [47] have shown the effect of not taking into account this kind of variables in the economic dispatch, and they propose to include the expected cost of balancing system deviations in the merit order dispatch to maintain an efficient delivery of energy. In the literature, authors have used several tools and methods to deal with stochastic variables and future events. Zhou et al. in [77] have used the point estimation method. In this method they find different deterministic scenarios according to the probability density function of wind speed, and minimize operational costs with security constraints. A multi-objective dispatch that considers uncertainty of wind generation have been proposed by Kargarian et al. in [35, 36]. The authors have minimized generation costs and the probability of network congestion, and have maximized the voltage stability margin. In [40], Lee et al. have used a decomposition algorithm that deals with a large scale stochastic environment. The authors have developed a frequency-constrained economic dispatch model, considering the uncertainty of wind energy and demand. Hargreaves et al. in [29] have proposed a dynamic programming model that optimizes both the stochastic UC and the dispatch of generators. The uncertainty of wind has been addressed in a two stage optimization problem that minimizes expected costs of operation. The uncertainty of demand response and load shedding has been analyzed by Zakariazadeh et al. in [73] and Murillo-Sanchez et al. in [48]. These researchers have used decomposition algorithms to find feasible deterministic scenarios. In summary, there are diverse methods to include future events and uncertain variables, but their main difference is the possibility to include different kinds of constraints, and the shape of the objective function. Saravanan et al. in [59] mention several techniques that have been applied by researchers to solve economic dispatch problems. On one hand, the main conventional techniques mentioned are: exhaustive enumeration, dynamic programming, priority listing, simulated annealing, Lagrangian relaxation, tabu search, branch and bound, and interior point optimization. On the other hand, the non-conventional techniques are: expert systems, fuzzy logic, neural networks, ant colony systems, and genetic algorithms.

Several authors have claimed that it is necessary to develop a dispatch model that includes behavior of future events and uncertainty of variables [3]. An application of this claim is in the smart grids area since its main components comprehend distributed generation (mainly renewable), electric vehicles, demand response programs, and energy storage systems. Altogether these elements compose what is known as distributed resources and are characterized as stochastic variables. The future behavior of smart grid elements may affect the present decisions of the system operator. Therefore, it is necessary a method that is able to include future events within the optimization problem whereas several constraints are included. This chapter presents an assessment of the MPC method in order to verify that it is an appropriate tool to solve the economic dispatch problem with several constraints while considering future events. The MPC is applied to a very simple example under three formulations: a standard system operator, a myopic system operator, and a non-myopic system operator.

This chapter is organized as follows. Section 2.2 presents the basic concepts of economic dispatch and the MPC method, along with their standard formulation. Different formulations for the economic dispatch problem are detailed in Section 2.3. Results of the proposed dispatch problems are presented in that section. Finally, Section 2.4 presents a brief discussion and some conclusions of this research.

2.2 Methodology

2.2.1 Economic dispatch

In the economic dispatch problem, the system operator finds the optimal output for each generator in the system. To that end, the operator takes as inputs the solution found in the UC and determines which is the best configuration of available machines for a specific time interval. The difference with respect to the UC problem is that economic dispatch would be solved for shorter periods with better (updated) information of demand, characteristics of generators, and network status. The solution of the economic dispatch must be found by optimizing an objective function and considering constraints. Usually, the system operator pursues operational costs minimization.

Power system operators dispatch generators economically in order to satisfy the load at every time step. In the economic dispatch problem, consider m generators in the set $\mathcal{N} = \{1, \ldots, m\}$, with individual generation limits $P_v^{\min}$ and $P_v^{\max}$, and ramping restrictions $\Delta P_v^{\min}$ and $\Delta P_v^{\max}$, where $v = 1, \ldots, m$. A time-variant load Q that must be satisfied by minimizing total generation costs calculated by $\sum_{v=1}^{m} C_v(P_{v,k}) = \sum_{v=1}^{m} a_v P_{v,k}^2 + b_v P_{v,k}.$:

$$\text{minimize} \quad \sum_{v=1}^{m} C_v(P_{v,k}) \tag{2.1a}$$

$$\text{s.t.} \quad \sum_{v=1}^{m} P_{v,k} = Q_k, \tag{2.1b}$$

$$P_v^{\min} \leq P_{v,k} \leq P_v^{\max}, \tag{2.1c}$$

In the demand constraint (2.1b), Q is the system demand and might be equal or different to the demand profile used in the UC problem. Finally, the constraint (2.1c) is related to the technical limits of power plants.

For simplicity, the economic dispatch problem is solved every hour (usually) for a specific demand Q_k. However, in order to include more constraints as in the UC problem, it is necessary to transform the dispatch problem formulation to consider a demand profile $[Q_k, \ldots, Q_{k+T}]$ instead of a single value. This modification allows the system operator to include intertemporal constraints such as:

- Ramp rate constraints

$$P_{v,k-1} - P_{v,k} \leq \Delta P_v^{\min}, \tag{2.2a}$$
$$P_{v,k} - P_{v,k-1} \leq \Delta P_v^{\max}. \tag{2.2b}$$

- Energy limited resources

$$\sum_{k=1}^{T} P_{v,k} \leq E_k \quad \forall v = 1, \ldots, m, \tag{2.3}$$

Moreover, additional constraints can be included in the optimization of the economic dispatch. These additional constraints can ensure that a solution is feasible from a technical perspective. The system operator might choose to include a frequency constraint, voltage stability constraint, security constraints (e.g., thermal capacity of elements), reliability constraints, environmental constraints, and so forth. Constraints of the economic dispatch can be the same kind as the constraints of the UC optimization problem. However, including all these constraints used in the UC leads to a very complex optimization problem, which demands high computational resources when applied to large scale systems. In this sense, it is necessary a more flexible optimization problem because operation horizon of economic dispatch is shorter than UC horizon. Thereby, economic dispatch can include a subset of constraints compromising to a lesser degree its time performance, even though the formulation becomes more complex.

2.2.2 Model Predictive Control

MPC is a method for controlling plants by solving an optimization problem with constraints on inputs and states, and it has been widely applied to industrial applications [42]. In this work we use MPC because it has some appropriate and interesting features for solving the dispatch problem. Case in point, there are some authors that have developed dispatch models with this non-classical method [46, 55, 61, 43, 79]. This control strategy allows the operator to consider future events and the evolution of the system in an optimization problem. For this purpose, an accurate model of the system is necessary, such that it represents the current status of the network and its evolution in terms of generation availability and demand. Furthermore, one of the main advantages of MPC is the possibility to include different kinds of constraints in the optimization problem. Generally, an MPC model can be defined as follows.

Consider a dynamic system given by the following representation:

$$x_{k+1} = Ax_k + Bu_k \tag{2.4a}$$
$$y_k = Cx_k + Du_k \tag{2.4b}$$

Then, the next optimization problem represents the optimality criteria of MPC:

$$\underset{\boldsymbol{u}}{\text{minimize}} \quad \sum_{j=0}^{Hp} ||\boldsymbol{e}_{k+j|k}||_{R_e} + ||\boldsymbol{u}_{k+j|k}||_{Q_u} \tag{2.5}$$
$$\text{s.t.} \quad x_i^- \leq x_i \leq x_i^+ \quad \forall i = 1, \dots, B \tag{2.5.a}$$
$$u_i^- \leq u_i \leq u_i^+ \quad \forall i = 1, \dots, U, \tag{2.5.b}$$

where $||\boldsymbol{e}_{k+j|k}||_{R_e} = \boldsymbol{e}^T_{k+j|k} R_e \boldsymbol{e}_{k+j|k}$ and $||\boldsymbol{u}_{k+j|k}||_{Q_u} = \boldsymbol{u}^T_{k+j1k} Q_u \boldsymbol{u}_{k+j|k}$. Here, B is the amount of state variables, and U is the amount of control variables. R_e is the weight matrix of error function, Q_u is the weight matrix of energy function, $r_{i,k+j}$ is the reference signal for state i. The prediction horizon H_p represents how long an operator can see in the future. Constraints in (2.5) are related to minimum and maximum levels of both the states and control signals. This formulation represents the MPC block shown in Fig. 2.1, which is the basic structure of an MPC scheme. First, the MPC solves an open-loop optimization problem applied to the virtual plant by considering reference signals for state variables. Second, the MPC applies an optimal control signal to the real plant and takes measures to update the virtual plant. This final stage is the closed-loop part of the MPC.

The MPC basic formulation (2.5) can be adapted to the formulation of the dispatch problem defined in this document. Given a control objective of economic dispatch the control inputs are computed by satisfying the following physical and operational

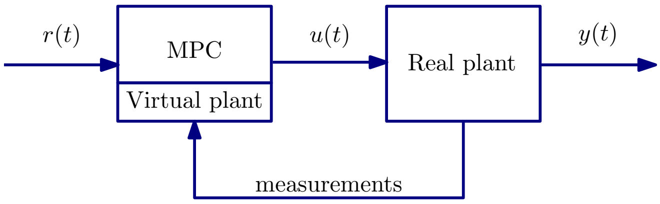


Fig. 2.1 MPC model, source [9].

constraints

$$\mathcal{P}_1 \triangleq \left\{ \boldsymbol{P} \in \mathbb{R}^m : \boldsymbol{P}^{\min} \leq \boldsymbol{P} \leq \boldsymbol{P}^{\max} \right\}, \tag{2.6a}$$

$$\mathcal{P}_2 \triangleq \left\{ \boldsymbol{P} \in \mathbb{R}^m : \Delta\boldsymbol{P}^{\min} \leq \Delta\boldsymbol{P} \leq \Delta\boldsymbol{P}^{\max} \right\}, \tag{2.6b}$$

$$\mathcal{P}_3 \triangleq \left\{ \boldsymbol{P} \in \mathbb{R}^m : \boldsymbol{P}^\top \mathbb{1}_m = Q \right\}. \tag{2.6c}$$

Let $\hat{\boldsymbol{P}}$ be the control input sequence for a fixed-time forecast period denoted by H_p, and let $\hat{Q}$ be the load sequence along H_p, i.e.,

$$\hat{\boldsymbol{P}}_k \triangleq \left(\boldsymbol{P}_{k|k}, \boldsymbol{P}_{k+1|k}, \ldots, \boldsymbol{P}_{k+H_p|k} \right), \tag{2.7a}$$

$$\hat{Q}_k \triangleq \left(Q_{k|k}, Q_{k+1|k}, \ldots, Q_{k+H_p|k} \right). \tag{2.7b}$$

The power system dispatch is controlled by an MPC controller whose optimization problem is to minimize a cost function, i.e.,

$$\underset{\hat{\mathbf{P}}}{\text{minimize}}\, J(\mathbf{P}), \tag{2.8a}$$

subject to

$$\mathbf{P}_{k+j|k} \in \bigcap_{l=1}^{3} \mathcal{P}_l, \quad j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}. \tag{2.8b}$$

Assuming that the optimization problem (2.8) is feasible, there is an optimal input sequence given by

$$\hat{\boldsymbol{P}}_k^\star \triangleq \left(\boldsymbol{P}_{k|k}^\star, \boldsymbol{P}_{k+1|k}^\star, \ldots, \boldsymbol{P}_{k+H_p|k}^\star \right).$$

and because only the first control input from the sequence $\hat{\boldsymbol{P}}_k^\star$ is applied to the system, then the final optimal control action is given by

$$\boldsymbol{P}_k^\star \triangleq \boldsymbol{P}_{k|k}^\star \in \bigcap_{l=1}^{3} \mathcal{P}_l.$$

Once the optimal control input $\boldsymbol{P}_k^\star$ is applied to the system and new information of the operational status is obtained through feedback, a new optimization problem of the form (2.8) is solved for iteration $k+1$, which leads to a new optimal sequence $\hat{\boldsymbol{P}}^\star$.

We have developed an MPC model for solving a very simple load balance problem to verify the functionality of this method. The proposed example has two generators without capacity constraints, but ramp constraints, and the system has a diary demand profile that the system operator knows beforehand. The MPC problem formulation is defined as follows:

$$\text{minimize} \quad \sum_{v=1}^{m}\sum_{j=0}^{Hp} P_{v,k+j|k} - Q_k \quad \forall\ k = 1,\dots,T \tag{2.9}$$

$$\text{s.t.} \quad P_{v,k+j-1|k} - P_{v,k+j|k} \leq \Delta P_v^{\min} \qquad v = 1,2 \tag{2.9.a}$$

$$P_{v,k+j|k} - P_{v,k+j-1|k} \leq \Delta P_v^{\max}. \tag{2.9.b}$$

The MPC optimization problem is solved with a genetic algorithm [30] that minimizes balance error between generation and demand, and creates feasible solutions that satisfy ramp rate constraints. Note that in this case the objective function does not consider energy costs, in contrast with the problem defined in (2.5). Fig. 2.2 shows obtained results when solving the load balance problem with an MPC approach. The blue line represents load profile of the system and dotted red line depicts the system generation. These two curves are superposed, which means that load and generation are balanced. From the results we can verify that an MPC approach is appropriate for solving dispatch problems because of its possibility to include constraints. In addition, the system operator would be able to look at the future for including certain and possible events in the optimization problem.

2.3 Case Study and Results

The economic dispatch task of the system operator and the main concepts of MPC have been explained in the previous section. Even though economic dispatch has been well addressed in traditional power systems, dispatch task in the presence of uncertain

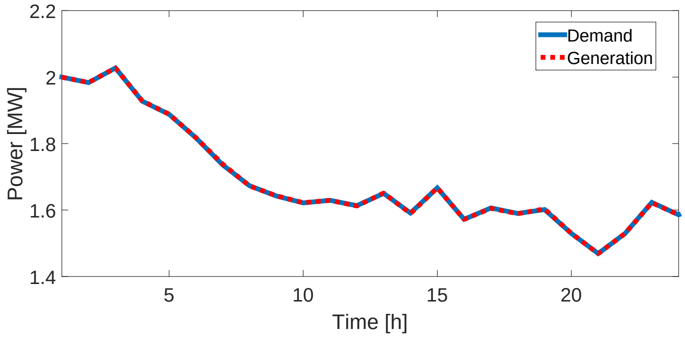


Fig. 2.2 Basic MPC performance.

variables has gathered significant interest of researchers because of the new elements to be considered (e.g., distributed resources and active participation of demand).

In section 2.1, it was mentioned that smart grids area is one of the most promising fields to implement algorithms that consider future events. Smart grid components have a common characteristic, their stochasticity. First, distributed generation mainly relies on renewable resources such as wind speed and solar radiation, which are very uncertain. Second, some demand response programs depend on the willingness of users to collaborate and receive incentives. Third, behavior of charging and discharging of electric vehicles is not always the same, and follows a random pattern. Finally, another very important stochastic variable is the network infrastructure availability since lines, transformers or generators might experience faults.

Integration of future events within the economic dispatch is essential since there are random variables that can be forecasted with a confidence level. In such case, the system operator may take preventive actions for dealing with possible changes in the network. Indeed, taking preventive actions is crucial because of the set of constraints in a dispatch problem. In this section, a simple case study is proposed and solved in order to analyze what is the impact of considering future events and their cost in the objective function, and how MPC seems appropriate to solve that kind of problem. To that end, we present three kinds of dispatch with their solution: i) dispatch without intertemporal constraints; ii) dispatch with intertemporal constraints, short-sighted operator; and iii) dispatch with intertemporal constraints, preventive operator. The case study (adapted from [11]) is characterized by the demand pattern presented in Fig. 2.3 and the generators to supply this demand (Table 2.1). The minimum capacity of generators is equal to zero in this exercise. The three kinds of dispatch are defined and solved as follows.

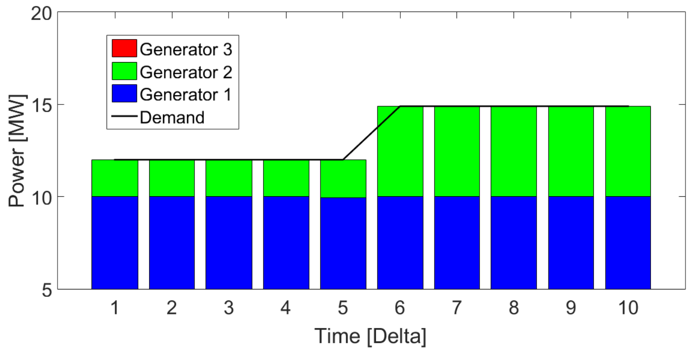


Fig. 2.3 Optimal dispatch without intertemporal constraints.

2.3.1 Dispatch without intertemporal constraints

In this case, the system operator aims to minimize operation costs for a single interval by considering two constraints: demand supply and capacity of power plants. Here, the system operator takes decisions without considering information of the past or probabilistic events of the future. Formulation of this optimization problem is defined as follows:

$$\begin{aligned} \underset{P_{v,k}}{\text{minimize}} \quad & \sum_{v=1}^{m} C_v(P_{v,k}) \\ \text{s.t.} \quad & \sum_{v=1}^{m} P_{v,k} = Q_k \quad \forall k = 1, \dots, T, \\ & P_v^{\min} \leq P_{v,k} \leq P_v^{\max} \quad \forall v = 1, \dots, n. \end{aligned}$$

Here, $C_v(P_{v,k}) = bP_{v,k}$ is a linear cost and $T = 10$ hours. This optimization problem has the same formulation presented in Section 2.2, Equation (2.1a), and its results are shown in Fig. 2.3. This figure shows the optimal generation pattern for each of the system generators. As it was expected, the cheaper generator is in the base, and when it reaches its maximum capacity, the second generator supplies the remaining demand because of the merit order. That is, when demand grows from 12MW to 14.9MW ($k = 6$) the second generator rises its generation to fulfill energy demand.

Table 2.1 Parameters of generators.

Generator	b \$/MWh	Maximum capacity(MW)	Ramp rate (MW/Δ_t)
1	10	10	1
2	20	5	0.75
3	100	20	20

2.3.2 Dispatch with intertemporal constraints, short-sighted operator

Although the system operator minimizes operation costs for a single interval in this formulation, the problem is solved for several intervals. In addition to the previous formulation, an intertemporal constraint is included such that the system operator takes decisions considering information of the past. Formulation of this optimization problem is defined as follows:

$$\begin{aligned}
\underset{P_{v,k}}{\text{minimize}} \quad & \sum_{v=1}^{m} C_v(P_{v,k}) \\
\text{s.t.} \quad & \sum_{v=1}^{m} P_{v,k} = Q_k \quad \forall k = 1, \dots, T, \\
& P_v^{\min} \leq P_{v,k} \leq P_v^{\max} \quad \forall v = 1, \dots, n, \\
& P_{v,k-1} - P_{v,k} \leq \Delta P_v^{\min} \qquad \forall v = 1, \dots, n, \\
& P_{v,k} - P_{v,k-1} \leq \Delta P_v^{\max} \qquad \forall v = 1, \dots, n.
\end{aligned}$$

The formulation of this dispatch has the objective function presented in Section 2.2, Equation (2.1a), and includes the ramp rate constraints detailed in (2.2a) and (2.2b). Fig. 2.4 shows the optimal solution of the economic dispatch when the system operator minimizes the costs of a single interval by taking into account ramp rate constraints. As well as in the previous optimization, the cheapest generator (generator 1) is the base power plant, and the second plant supplies the remaining demand. However, when load grows in $k = 6$ the second generator does not supply instantaneously the remaining demand because of its ramp limitation. The solution in this case is to dispatch the most expensive power plant (generator 3) for meeting demand requirements from $k = 6$ to $k = 8$.

2.3.3 Dispatch with intertemporal constraints, preventive operator

In contrast to the previous dispatch, the system operator aims to minimize operation costs not only for a single interval but for an operation horizon. Here, the system operator includes information of the past in constraints, and certain events of the future in the objective function. This optimization problem allows the operator to take better actions in the present by considering future events, as it has been shown by Wu et al. in [68]. For simplicity and to show the importance of avoiding a myopic operator, it is assumed that there is complete certainty about future events (i.e. the increase of demand in $k = 6$). Formulation of this optimization problem is defined with the structure of an MPC as follows:

$$\begin{aligned} \underset{P_{v,k+j|k}}{\text{minimize}} \quad & \sum_{v=1}^{m}\sum_{j=0}^{H_p} C_v(P_{v,k+j|k}) \\ \text{s.t.} \quad & \sum_{v=1}^{m} P_{v,k+j|k} = Q_{k+j|k} \qquad \forall k = 1,\dots,T \\ & P_v^{\min} \leq P_{v,k+j|k} \leq P_v^{\max} \quad \forall v = 1,\dots,n, \\ & P_{v,k+j-1|k} - P_{v,k+j|k} \leq \Delta P_v^{\min} \qquad \forall v = 1,\dots,n, \\ & P_{v,k+j|k} - P_{v,k+j-1|k} \leq \Delta P_v^{\max} \qquad \forall v = 1,\dots,n. \end{aligned}$$

The difference in this formulation with respect to the previous case is the summation over the operation horizon in the objective function. Fig. 2.5 shows the optimal generation for supplying the demand pattern when the system operator includes future costs along with ramp rate constraints, and its prediction horizon is equal to 5. Results show that generator 1 is the base generator, but reduces its output from $k = 4$ in order to ramp up generator 2. This decision anticipates load growth at $k = 6$ such that the most expensive generator only operates at $k = 6$. Thereby operational costs from $k = 6$ to $k = 8$ are minimized as it is shown in Fig. 2.6.

Hourly operational costs and cumulative costs of the analyzed optimization problems are shown in Fig. 2.6. Dispatch without intertemporal constraints has the best costs performance, but this is not a common scenario because of the ramp rate constraints. When ramp rate constraints are included, operational and cumulative costs increase because generator 3 (the most expensive) must be dispatched. However, operational and cumulative cost can be reduced if future costs are included in the objective function.

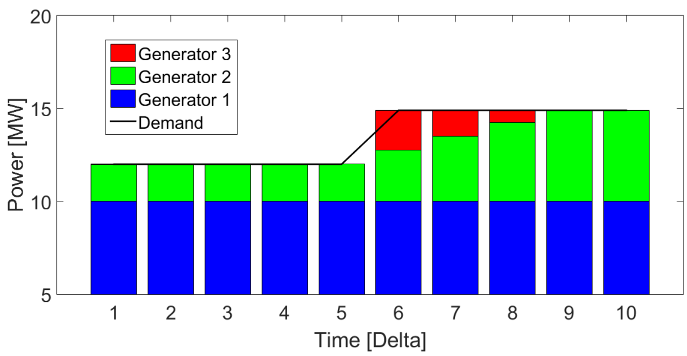


Fig. 2.4 Optimal dispatch with intertemporal constraints and a myopic operator.

A non-myopic operator can anticipate forthcoming events and mitigate future costs by adjusting current set points although operating with a suboptimal solution. Case in point (Fig. 2.6a), operational costs for non-myopic system operator are higher than costs of myopic system operator from $k = 4$ to 5. Nevertheless, operational costs for non-myopic system operator are lower than costs of myopic system operator from $k = 6$ to 8. In terms of the cumulative costs (Fig. 2.6b), it is verified that a non-myopic operator performs better as a result of anticipating future events.

2.4 Concluding Remarks and Discussion

From this research we wanted to show that MPC is a promising method to deal with economic dispatch problems that might include information of future events. To that end, three different perspectives of a system operator were formulated as optimization problems and applied to a case study. The case study was composed by three generators with capacity limits and ramp rate constraints.

MPC was efficiently tested in the economic dispatch environment and seems appropriate to deal with new requirements of the electric system operation. This is the consequence of including several types of constraints in the MPC problem, and its ability to optimize an objective function with future information. Considering these features, a smart grid is the perfect scenario to implement this kind of solution due to the stochastic behavior of its components, and the constraints of the network. In addition, this method can be useful for real time applications or very short term dispatch problems.

The importance of taking preventive actions has been shown in the case study, where a system operator obtains better results when considering future events. In a stochastic environment the system operator may not be able to have complete knowledge of

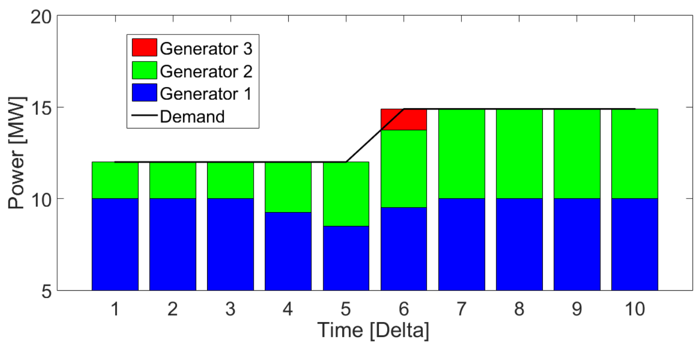
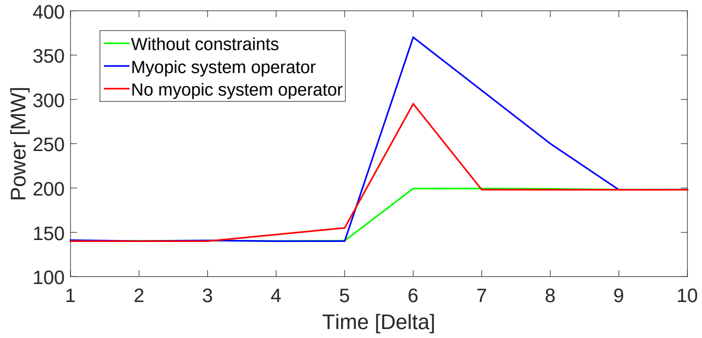
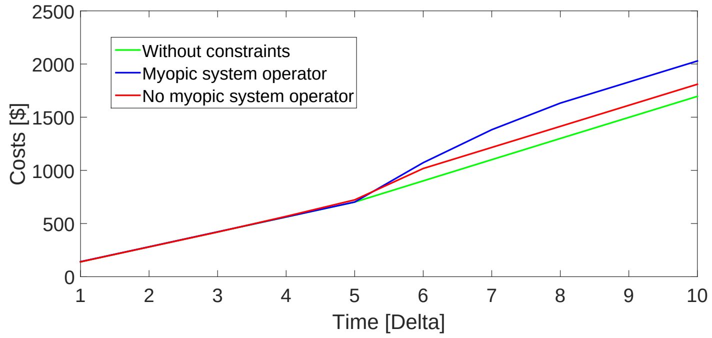


Fig. 2.5 Optimal dispatch with intertemporal constraints and non-myopic operator.



(a) Normal



(b) Fault

Fig. 2.6 Results of analyzed dispatch problems. a) Hourly operational costs. b) Cumulative costs.

the system variables. However, the operator can consider different scenarios with a probability level such that expected value of future costs is obtained. This is one topic that we have addressed on this thesis.

Chapter 3

Consensus-Based Distributed Model Predictive Control for Power System Economic Dispatch

Distributed generation entities such as renewable energy sources have posed great challenges on power system economic dispatch because of their output variability and stochasticity. Accordingly, operators need to lessen unpredictable changes in scheduled generation settings by fully utilizing available forecast information in the decision-making process. This chapter proposes a closed-loop algorithm for realizing economic dispatch at runtime while reducing potential deviations of generation schedules. At first, a traditional centralized approach to solving the economic dispatch problem is presented with discussions on potential enhancement enabled by model predictive control techniques. The MPC application makes it possible for operators to address the concern of variability and stochasticity. This chapter then develops a dual decomposition-based distributed model predictive control strategy that is compatible with consensus techniques. It is also discussed that communication requirements of the proposed DDMPC are less strict than its centralized counterpart. The simulation results validate the advantages of the proposed DDMPC approach by comparing it with traditional techniques for economic dispatch.

3.1 Introduction

Power system is a large and complex control system that has been increasingly faced with challenges of generation variability as a multitude of renewable energy resources are accommodated in the power system operation. As a response to such uncertain operating condition, power system operators optimize the commitment and dispatch of generators for supplying the electricity demand while respecting all physical and operational requirements. In most cases, power system operators have an objective of minimizing system operation costs with the consideration of specific constraints of generation and transmission resources. Power system operation costs are mainly caused by utilizing generation resources including fuel costs, opportunity costs, crew costs, as well as equipment maintenance costs.

This chapter is focused on the economic dispatch of generation resources, which is an optimization-based control problem that aims to meet short-term (e.g., hourly, 15-minute, 5-minute) load requirements economically. The economic dispatch is conventionally solved by a central operator that collects technical and operational information from participating generators in order to obtain efficient solutions. Although a centralized approach is often rigorous, its control system configuration requires a more complex communication network architecture that could be costly and inefficient for large-scale power systems, especially those with a remotely-located central control system. However, an advantage of a centralized approach is that system operators schedule all generators so that they are dispatched to minimize power system operation costs. For instance, a base generator decreases its power output so a ramp-constrained generator can increase its production level as the system load increases. That behavior is not the natural response of a generator, but the system operator can command the set point of a power plant according to economic and technical characteristics.

On the other hand, distributed control methods have a simpler communication network requirement since individual controllers do not communicate with each other or with a central operator to solve the optimization problem for achieving the stated control objectives in power systems. Moreover, a distributed approach enables parallel optimization, so computational time decreases. However, the distributed control design is quite challenging when considering coupled dynamic behaviors of individual controllers. Furthermore, calculating an efficient solution that meets load requirements for the distributed controller problem is difficult when the sharing of operation information of individual controllers is restricted. In [16] and [49], there is a discussion on the distributed model of predictive control. As an alternative, a decomposition of the overall control problem into smaller decoupled problems and the corresponding coordination of components in a centralized manner is presented in [19].

In addition to selecting the appropriate control strategy and a certain type of dispatch architecture, power system operators consider possible scenarios pertaining to uncertain variables. These uncertain variables may have different effects on the economic dispatch constraints. Technical constraints are presented in both single-interval and multi-interval forms. The former constraints include the generating units capacity, hourly loads, and network security constraints. The latter constraints comprise ramp-rate limits, minimum on/off time, and energy-limited resources capacity (e.g., batteries). In addition, variable resources (e.g., wind, hydro, solar) are introducing new challenges to power system operators. By using forecasting models and optimization schemes that consider stochastic scenarios, power system operators strive to commit or dispatch thermal plants that can balance variable power supplies and minimize operating costs [47].

In this chapter, we consider a model predictive control design for calculating the centralized economic dispatch for power systems in a distributed manner. The MPC studies on the power system economic dispatch problem include both centralized and distributed control strategies. Considering centralized approaches, Abdeltawab et al. in [1] proposed an energy management system for a hybrid power system with wind generation and energy storage. MPC was considered by Kim et al. in a dynamic economic dispatch approach [37]. In [78], Zhu et al. proposed a switched MPC model, for managing photovoltaic systems with storage devices, which considers switched constraints instead of a switched state space model. Mayhorn et al. [44] proposed an MPC to integrate wind power plants by using a combined diesel generator and an energy storage system for coordination. A game theory-based demand response approach was proposed and analyzed by Nwulu et al. in [50]. In [63], Torreglosa et al. presented an energy dispatch based on MPC for an off-grid hybrid system with hydrogen storage. Zheng et al. in [75] developed a heuristic MPC with a differential evolution algorithm to manage an energy storage system. Considering distributed approaches, Ilić et al. in [31] proposed a method known as DYMONDS, which has both centralized and distributed features. They showed that a fully distributed algorithm may not reach a balance between generation and demand. The authors applied MPC to solve economic and environmental dispatch problems with intermittent generation resources [72]. Del Real et al. in [2] designed a distributed MPC based on Lagrange-MPC. The proposed optimization problem minimized both economic and environmental costs in interconnected energy hubs. Although researches on distributed MPC for the economic dispatch have made very interesting contributions, to the best of our knowledge there are some points that are not addressed completely. That is, quality of solution compared to a centralized MPC and granularity of agents.

In this chapter we propose a distributed approach for the economic dispatch problem in order to tackle the curse of dimensionality commonly seen in stochastic approaches. The distributed MPC uses dual decomposition along with an average consensus algorithm. Since a fully distributed approach without a coupling balance constraint will deviate from an appropriate operation point [31], the main contribution of this research is to balance power generation and load demand in a distributed approach that emulates the centralized solution. A centralized solution is known as the benchmark because of the existence of a central controller with full information [31]. Emulation of the centralized dispatch is a complicate task since a generator might require other generators' unpublished cost and production data. In an MPC approach, we provide a distributed economic dispatch solution with a coupling balance constraint which will not require any private information, as one contribution of this work. The proposed formulation is solved by every power plant in the network such that granularity of agents is enhanced.

The remainder of this chapter is organized as follows. In Section 3.2 the background of MPC, dual decomposition, and distributed dual decomposition is provided. Section 3.3 describes the problem statement for both centralized and distributed approaches. The results of case studies are presented in Section 3.4, along with a justification of why it is better to use MPC instead of traditional approaches. Finally, in Section 3.5 conclusions are drawn.

3.2 Problem Formulation and Mathematical Background

Power system operators dispatch generators economically in order to satisfy the load at every time step. In this economic dispatch problem, consider n generators in the set $\mathcal{C} = \{1, \ldots, n\}$, with individual generation limits $P_\ell^{\min}$ and $P_\ell^{\max}$, and ramping restrictions $\Delta P_\ell^{\min}$ and $\Delta P_\ell^{\max}$, where $\ell = 1, \ldots, n$. A time-variant load Q that must be satisfied by minimizing total generation costs calculated by $\sum_{\ell=1}^{n} C_\ell(P_{\ell,k}) = \sum_{\ell=1}^{n} a_\ell P_{\ell,k}^2 + b_\ell P_{\ell,k}$. For solving such optimization problem in a distributed manner, we use the MPC method, the Lagrangian dual decomposition, and the average consensus algorithm that are described as follows:

3.2.1 Dual decomposition

Dual decomposition is performed by utilizing the Lagrangian function corresponding to the original optimization problem [14]. Consider an optimization problem $\text{minimize}_{\boldsymbol{P}}\ J(\boldsymbol{P})$ with a coupled constraint $\sum_{\ell=1}^{n} P_\ell = Q$. Then, the Lagrangian function with mapping $L : \mathbb{R}^n \times \mathbb{R} \rightarrow \mathbb{R}$ is defined as

$$L(\boldsymbol{P}, \mu) = J(\boldsymbol{P}) + \mu \left(\sum_{\ell=1}^{n} P_\ell - Q \right), \tag{3.1}$$

where $\mu \in \mathbb{R}$ is to the Lagrange multiplier associated with the coupled constraint. The dual decomposition iterative procedure is then stated as:

$$\boldsymbol{P}_{\tilde{k}+1} = \arg \underset{\boldsymbol{P}_{\tilde{k}}}{\text{minimize}}\ L(\boldsymbol{P}_{\tilde{k}}, \mu_{\tilde{k}}), \tag{3.2a}$$

$$\mu_{\tilde{k}+1} = \mu_{\tilde{k}} + \alpha \left(\sum_{\ell=1}^{n} P_{\ell,\tilde{k}+1} - Q \right), \tag{3.2b}$$

For convenience, equation (3.2b) is rewritten as:

$$\mu_{\tilde{k}+1} = \mu_{\tilde{k}+1} + \alpha \left(\boldsymbol{P}_{\tilde{k}+1}^{\top} \mathbb{1}_n - Q \right). \tag{3.3}$$

To start the procedure, the value of the Lagrange multiplier is initialized in the feasible range $\mu_0 \in \mathbb{R}$. Then, the optimization problem (3.2a) is solved to find $\boldsymbol{P}_{\tilde{k}+1}$ so as to update the Lagrange multiplier through (3.2b). Equations (3.2a) and (3.2b) are solved iteratively until convergence is satisfied. Since $\tilde{\Delta t} << \Delta t$, the Lagrangian iterative process is always performed before new information of the system is available.

3.2.2 Distributed dual decomposition algorithm

Consider a connected and undirected communication graph denoted by $\mathcal{G} = (\mathcal{C}, \mathcal{E})$, where each node (generator) is designated a decision variable denoted by P_ℓ. As can be proved by the graph theory, the existence of the coupled constraint (3.2b) will result in a centralized dual decomposition algorithm, i.e., all information from $P_{\ell,\tilde{k}+1}$, for all $\ell \in \mathcal{C}$, will be required to update the Lagrange multiplier $\mu_{\tilde{k}+1}$. However, for an optimization problem with a specific coupled constraint, it is possible to implement the dual decomposition algorithm (3.2) in a distributed manner. The main idea is to add an additional step in the dual decomposition algorithm by computing $\sum_{\ell=1}^{n} P_{\ell,\tilde{k}+1}$ in a distributed manner. So, the distributed algorithm would be: solve the Lagrangian dual subproblem (3.2a) first, then find $\sum_{\ell=1}^{n} P_{\ell,\check{k}+1}$ with an average-consensus algorithm, and finally update the Lagrange multiplier (3.2b). Thereby, the following average-consensus algorithm is considered for our study.

Let $\boldsymbol{\xi} \in \mathbb{R}^n$ be a vector of auxiliary variables, i.e., $\xi_\ell \in \mathbb{R}$ corresponding to a node $\ell \in \mathcal{C}$. The variables are initialized according to the results obtained from (3.2a), i.e., $\xi_{\ell,0} = P_{\ell,\check{k}+1}$, for all $\ell \in \mathcal{C}$. Next, a continuous-time standard average consensus algorithm is performed iteratively until convergence is achieved (convergence proofs of the algorithm are addressed by Xiao et al. in [71]). The consensus equation is defined as:

$$\xi_{\ell,\check{k}+1} = \xi_{\ell,\check{k}} + \sum_{i \in \mathcal{N}_\ell} w_{\ell i} \left(\xi_{i,\check{k}} - \xi_{\ell,\check{k}} \right), \quad \forall \ell \in \mathcal{C} \tag{3.4}$$

where $w_{\ell i}$ is the weight of the link between nodes ℓ and i. Since the graph is undirected, $w_{\ell i} = w_{i\ell}$. Here, $\check{k}$ is the discrete time for a sampling time very close to zero. If the communication graph $\mathcal{G}$ is connected, and the weight of links are symmetrical, then the dynamics in (3.4) converge to $\boldsymbol{\xi}^\star \in \mathbb{R}^n$, where $\xi^\star_\ell = \sum_{\ell \in \mathcal{C}} \xi_{\ell,0}/n$, for all $\ell \in \mathcal{C}$ [51]. Equivalently,

$$n\xi^\star_\ell = \sum_{\ell \in \mathcal{C}} P_{\ell,\check{k}+1}, \quad \text{for all } \ell \in \mathcal{C},$$

Accordingly, each node in graph $\mathcal{G}$ offers data for calculating $\sum_{\ell=1}^{n} P_{\ell,\check{k}+1}$ and updating the Lagrange multiplier in a distributed manner.

3.3 Economic Dispatch Alternatives

Consider the following optimization problems that address the optimal power allocation and that are characterized by the control architectures depicted in Fig. 3.1.

3.3.1 Traditional Dynamic Power Dispatch

In practice, power system operators minimize system operation costs in a multi-interval period by considering prevailing constraints on load, supply, generator capacity, and ramping rates [12], as shown below:

$$\underset{P_{\ell,k}}{\text{minimize}} \quad \sum_{\ell=1}^{n} C_\ell(P_{\ell,k}) \tag{3.5a}$$

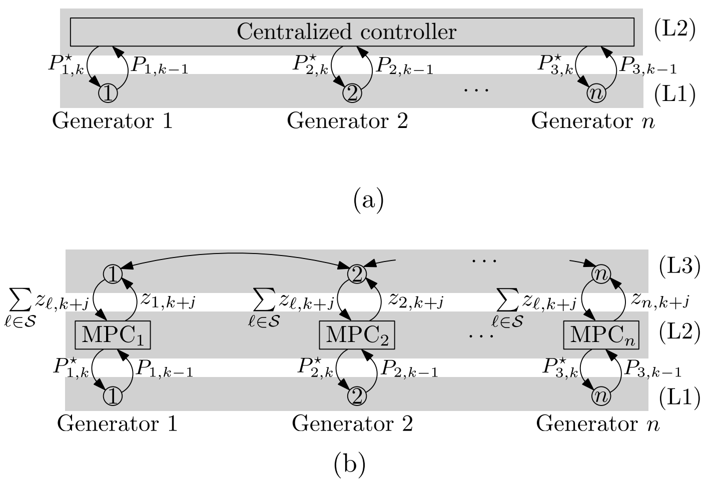


Fig. 3.1 Control schemes for both centralized and distributed configuration. (a) Scheme for n generators corresponding to dynamic and centralized MPC-based dispatch composed of two layers: (L1) physical layer, and (L2) control layer. (b) DDMPC scheme for n generators composed of three layers: (L1) physical layer, (L2) control layer, and (L3) consensus layer.

subject to

$$\sum_{\ell=1}^{n} P_{\ell,k} = Q_k, \tag{3.5b}$$

$$P_\ell^{\min} \le P_{\ell,k} \le P_\ell^{\max}, \tag{3.5c}$$

$$\Delta P_\ell^{\min} \le \Delta P_{\ell,k} \le \Delta P_\ell^{\max}. \tag{3.5d}$$

The optimization problem (3.5) is solved at every time instant $k = 1, \ldots, T$, with the consideration of generators' ramping capabilities. The balance constraint (3.5b) must be considered for all $k \in [1, T] \cap \mathbb{Z}_{\ge 0}$, whereas constraints (3.5c) and (3.5d) representing generators' physical characteristics are necessary for all $\ell \in \mathcal{C}$, $k \in [1, T] \cap \mathbb{Z}_{\ge 0}$. Note that if the optimization problem (3.5) does not consider generators' ramping capabilities (3.5d), it turns into a static economic dispatch problem that is independent at each time instant. However, a dispatch plan is not practically implementable if the temporal correlation of generators' power outputs, as constrained by their physical characteristics, is ignored. Even though the dynamic power dispatch respects all physical charactersitics, it might not be economic due to the fact that total costs over the operation horizon are not optimized holistically. This issue can be avoided if forecasted data representing future loading conditions in the subsequent time intervals is considered in the optimization problem (3.5). There have been some methods such as dynamic programming, MPC, and scenario decomposition, taking advantage of forecasted information in order to find optimal solutions at present through the perception of future conditions.

MPC methods have been sucessfully applied to common industrial applications like process control. MPC applications in power systems have been intensified within the last few years, given the increasing implementation of distributed generation technologies such as roof-top solar panels and local energy storage devices. Traditional approaches for economic dispatch commonly find the optimal solution for a single interval in an off-line fashion. However, with the presence of more disturbances in the system operation due to the stochastic nature of renewable resources, off-line open-loop methods have lost efficiency and accuracy. One alternative is to implement stochastic approaches for coping with uncertainties in the system operation, but most stochastic approaches (e.g., scenario decomposition) still determine the optimal solution in an off-line fashion since an on-line feedback policy is very difficult or impossible to implement (e.g., dynamic programming), especially in the presence of inter-temporal constraints. On the other hand, MPC methods solve an open-loop finite-horizon control problem in real time for the current state of the system. Once new measurements and forecast information of the system operating condition are available, a new open-loop finite-horizon optimization problem with updated initial conditions is solved. In particular, forecast information of stochastic variables helps operators find the optimal solution in the current state. Since MPC considers the impact of future conditions in the present operation, constraints can be included in the optimization problem more flexibly. Hence, MPC is known as an on-line closed-loop method that is capable of mitigating the risk of variability and uncertainty, and its response to large disturbances can be further improved by incorporating stochastic methods.

3.3.2 Centralized Model Predictive Control

A centralized MPC approach can obtain the optimal dispatch solution as the centralized controller has information of every agent for maximizing the global benefit, e.g., minimizing total operation costs. In this case, the optimization model is formulated as:

$$\underset{P_{\ell,k+j|k}}{\text{minimize}} \sum_{\ell=1}^{n} \sum_{j=0}^{H_p} C(P_{\ell,k+j|k}), \tag{3.6a}$$

subject to

$$\sum_{\ell=1}^{n} P_{\ell,k+j|k} = Q_{k+j|k}, \tag{3.6b}$$

$$P_{\ell,k+j}^{\min} \leq P_{\ell,k+j|k} \leq P_{\ell,k+j}^{\max}, \tag{3.6c}$$

$$\Delta P_{\ell,k+j}^{\min} \leq \Delta P_{\ell,k+j|k} \leq \Delta P_{\ell,k+j}^{\max}. \tag{3.6d}$$

The MPC controller computes an optimal sequence for the control inputs denoted by $\hat{\boldsymbol{P}}_k^\star$, where $\boldsymbol{P}_{k+j|k} = [P_{1,k+j|k} \quad \ldots \quad P_{n,k+j|k}]^\top$. Only the first control input from the optimal sequence is applied to the system $\boldsymbol{P}_k^\star \triangleq \boldsymbol{P}_{k|k}^\star$. (3.6b) must be satisfied for all $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$, and (3.6c) and (3.6d) are required for all $\ell \in \mathcal{C}$, $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$. The Lagrangian function associated with the optimization problem (3.6) is

$$\begin{aligned} L(\boldsymbol{P}, \Lambda, \boldsymbol{\Psi}) = \sum_{\ell=1}^{n} \sum_{j=0}^{H_p} & C(P_{\ell,k+j|k}) - \\ & \lambda_{k+j} \left(\sum_{\ell=1}^{n} P_{\ell,k+j|k} - Q_{k+j|k} \right) + \psi_{\ell,k+j}^1 \left(P_{\ell,k+j}^{\min} - P_{\ell,k+j|k} \right) \\ & + \psi_{\ell,k+j}^2 \left(P_{\ell,k+j|k} - P_{\ell,k+j}^{\max} \right) + \psi_{\ell,k+j}^3 \left(\Delta P_{\ell,k+j}^{\min} - \Delta P_{\ell,k+j|k} \right) \\ & + \psi_{\ell,k+j}^4 \left(\Delta P_{\ell,k+j|k} - \Delta P_{\ell,k+j}^{\max} \right), \end{aligned} \tag{3.7}$$

where λ_{k+j} is the Lagrange multiplier of the coupled equality constraint (3.6b), $\psi_{\ell,k+j}^1$ and $\psi_{\ell,k+j}^2$ are Lagrange multipliers of constraints (3.6c), and $\psi_{\ell,k+j}^3$ and $\psi_{\ell,k+j}^4$ are Lagrange multipliers of constraints (3.6d). The corresponding Karush-Kunh-Tucker conditions are given by

$$\begin{aligned} \nabla_{P_{\ell,k+j|k}} L(\boldsymbol{P}^\star, \Lambda^\star, \boldsymbol{\Psi}^\star) = & \frac{\partial C(P_{\ell,k+j|k}^\star)}{\partial P_{\ell,k+j|k}} - \lambda_{k+j}^\star - \psi_{\ell,k+j}^{1,\star} \\ & + \psi_{\ell,k+j}^{2,\star} - \psi_{\ell,k+j}^{3,\star} + \psi_{\ell,k+j}^{4,\star} = 0, \end{aligned} \tag{3.8a}$$

$$Q_{k+j|k} = \sum_{\ell=1}^{n} P^{\star}_{\ell,k+j|k}, \tag{3.8b}$$

$$0 \leq \psi^{1\star}_{\ell,k+j}, \psi^{2\star}_{\ell,k+j}, \psi^{3\star}_{\ell,k+j}, \psi^{4\star}_{\ell,k+j}, \tag{3.8c}$$

$$0 = \psi^{1\star}_{\ell,k+j} \left(P^{\min}_{\ell,k+j} - P^{\star}_{\ell,k+j|k}\right), \tag{3.8d}$$

$$0 = \psi^{2\star}_{\ell,k+j} \left(P^{\star}_{\ell,k+j|k} - P^{\max}_{\ell,k+j}\right), \tag{3.8e}$$

$$0 = \psi^{3\star}_{\ell,k+j} \left(\Delta P^{\min}_{\ell,k+j} - \Delta P^{\star}_{\ell,k+j|k}\right), \tag{3.8f}$$

$$0 = \psi^{4\star}_{\ell,k+j} \left(\Delta P^{\star}_{\ell,k+j|k} - \Delta P^{\max}_{\ell,k+j}\right). \tag{3.8g}$$

Here, constraints (3.8b)-(3.8g) must hold for all $\ell \in \mathcal{C}$, $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$. Fig. 3.1(a) shows the control scheme corresponding to the centralized model predictive control.

A CMPC might not be manageable in a large-scale system due to the curse of dimensionality resulting from the huge number of decision variables in a multi-interval period. This is a big barrier for on-line applications of the short-term economic dispatch. This issue is even more restraining when stochastic approaches are employed instead of deterministic programs. For example, an MPC with prediction horizon H_p and m generators has $m(H_p+1)$ decision variables, which is intractable in large power systems, even in a deterministic optimization framework. In an uncertain environment, scenario decomposition for instance, the MPC with $m(H_p+1)$ decision variables must be solved for every scenario. The number of scenarios depends on the number of stochastic variables (e.g., renewable generators): the greater the number of renewable generators, the greater the amount of scenarios. Therefore, the problem complexity increases with the amount of decision variables and scenarios. To solve such a high-dimensionality problem, a distributed MPC is proposed in this chapter.

3.3.3 Distributed Dual decomposition-based Model Predictive Control

In addition to the benefits of having a smaller communication network and less dependence on a centralized controller, the amount of decision variables and scenarios significantly decrease in each distributed problem. Since the optimal output is found locally in a DDMPC, there are $H_p + 1$ decision variables and stochastic scenarios are defined by considering the local data, i.e., without considering uncertainty from other generators. However, maximization of global benefit and fulfillment of coupled constraints are challenging in a DDMPC. The proposed DDMPC achieves both objectives. First, global benefit is maximized in DDMPC since its objective function is derived as the dual problem of costs minimization in CMPC through KKT conditions. Second, the coupled constraint associated to the system-wide energy balance is achieved by finding its Lagrange multiplier through a consensus algorithm.

The optimization problem (3.6) is solved in a distributed manner by applying dual decomposition and consensus in order to deal with the coupled constraint (3.8b). Hence, we assume that all generators $\ell \in \mathcal{C}$ know the forecasted system load at time instant $k \in \mathbb{Z}_{\geq 0}$, i.e., $Q_{k+j|k}$, for all $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$. Note that this assumption is reasonable since it is only necessary that at least one generator knows the forecasted load, and then broadcasts the information to all generators in a distributed manner based on a consensus algorithm [51]. Consider the distributed MPC controller for each generator $\ell \in \mathcal{C}$ whose optimization problem is given by

$$\begin{aligned} \underset{P_{\ell,k+j|k}}{\text{minimize}}\ J_\ell(P_{\ell,k+j|k}, \boldsymbol{\lambda}_k) = \sum_{j=0}^{H_p} \Bigg\| & \frac{\partial C(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}} \\ & - \lambda_{k+j} - \psi^1_{\ell,k+j} + \psi^2_{\ell,k+j} - \psi^3_{\ell,k+j} + \psi^4_{\ell,k+j} \Bigg\|^2, \end{aligned} \tag{3.9a}$$

subject to

$$P^{\min}_{\ell,k+j} \leq P_{\ell,k+j|k} \leq P^{\max}_{\ell,k+j}, \tag{3.9b}$$
$$\Delta P^{\min}_{\ell,k+j} \leq \Delta P_{\ell,k+j|k} \leq \Delta P^{\max}_{\ell,k+j}, \tag{3.9c}$$
$$0 \leq \psi^1_{\ell,k+j}, \psi^2_{\ell,k+j}, \psi^3_{\ell,k+j}, \psi^4_{\ell,k+j}, \tag{3.9d}$$
$$0 = \psi^1_{\ell,k+j}\left(P^{\min}_{\ell,k+j} - P_{\ell,k+j|k}\right), \tag{3.9e}$$
$$0 = \psi^2_{\ell,k+j}\left(P_{\ell,k+j|k} - P^{\max}_{\ell,k+j}\right), \tag{3.9f}$$
$$0 = \psi^3_{\ell,k+j}\left(\Delta P^{\min}_{\ell,k+j} - \Delta P_{\ell,k+j|k}\right), \tag{3.9g}$$
$$0 = \psi^4_{\ell,k+j}\left(\Delta P_{\ell,k+j|k} - \Delta P^{\max}_{\ell,k+j}\right), \tag{3.9h}$$

where $\hat{P}_{\ell,k} = \left(P_{\ell,k|k}, \ldots, P_{\ell,k+H_p|k}\right)$ is the sequence of control inputs for generator $\ell \in \mathcal{C}$, and $\boldsymbol{\lambda}_k = [\lambda_k \quad \ldots \quad \lambda_{k+H_p}]^\top \in \mathbb{R}^{H_p+1}$. The constraints (3.9b)-(3.9h) must be satisfied for all $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$. The Lagrange multipliers $\boldsymbol{\lambda}_k = \boldsymbol{\varepsilon}^\star$, for $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$ are computed according to the dual decomposition algorithm. Let $\boldsymbol{z}_\ell = \begin{bmatrix} P^\star_{\ell,k|k} & P^\star_{\ell,k+1|k} & \ldots & P^\star_{\ell,k+H_p|k}\end{bmatrix}^\top$ be a vector of auxiliar variables defined as $\boldsymbol{z}_\ell = \arg\text{minimize}_{P_{\ell,k+j|k}} \sum_{j=0}^{H_p} J_\ell(P_{\ell,k+j|k}, \boldsymbol{\lambda}_k)$, where $\boldsymbol{z}_\ell \in \mathbb{R}^{H_p+1}$. In addition, we define the matrix $\boldsymbol{Z} = [\boldsymbol{z}_1 \quad \ldots \quad \boldsymbol{z}_n] \in \mathbb{R}^{H_p+1\times n}$. Then, the dual decomposition algorithm at the time instant k, is computed as

$$\boldsymbol{z}_{\ell,\tilde{k}+1} = \arg \underset{P_{\ell,k+j|k}}{\text{minimize}} \sum_{j=1}^{H_p} J_\ell(P_{\ell,k+j|k}, \boldsymbol{\varepsilon}_{\tilde{k}}), \quad \forall \ell \in \mathcal{C}, \tag{3.10a}$$

$$\boldsymbol{\varepsilon}_{\tilde{k}+1} = \boldsymbol{\varepsilon}_{\tilde{k}} + \alpha \left(\boldsymbol{Z}_{\tilde{k}+1} \mathbb{1}_n - \boldsymbol{q}_k \right), \tag{3.10b}$$

where $\boldsymbol{\varepsilon}_{\tilde{k}} = [\varepsilon_{0,\tilde{k}} \quad \ldots \quad \varepsilon_{H_p,\tilde{k}}]^\top \in \mathbb{R}^{H_p+1}$, $\boldsymbol{Z}_{\tilde{k}+1} = [\boldsymbol{z}_{1,\tilde{k}+1} \quad \ldots \quad \boldsymbol{z}_{n,\tilde{k}+1}] \in \mathbb{R}^{H_p+1\times n}$, $\boldsymbol{q}_k = [Q_{k|k} \quad \ldots \quad Q_{k+H_p|k}]^\top \in \mathbb{R}^{H_p+1}$, $\alpha \in \mathbb{R}_{\geq 0}$ is a constant value, and $\boldsymbol{Z}_{\tilde{k}+1}\mathbb{1}_n$, in (3.10b) is computed in a distributed manner by using the average consensus algorithm for all $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$. The vector $\boldsymbol{\varepsilon}^\star$ corresponds to the convergence values of the iterative equation (3.10b).

In summary, the centralized MPC shown in (3.6) is solved in a distributed manner by solving the local MPC problem presented in (3.9) which applies the updated Lagrange multiplier. The update of multipliers is done by using consensus which corresponds to the equality constraint (3.8b). Fig. 3.1(b) shows the DDMPC scheme by using distributed dual decomposition with consensus. The DDMPC iterative process of each generator for solving the economic dispatch is depicted in Fig. 3.2. The iterative process is terminated when either the limit of iterations is achieved or the updated value of the Lagrange multiplier remains the same for a certain number of iterations.

3.4 Case Studies and Results

This section provides the results of case studies to show the benefits of using a DDMPC approach in comparison with other alternatives to solve the economic dispatch.

3.4.1 Comparison of DDMPC with Traditional Dynamic Power Dispatch and DYMONDS

Two different load scenarios for three heterogenous generators $\mathcal{C} = \{1, 2, 3\}$ are defined and tested in order to highlight the advantages of implementing a distributed MPC controller for the economic dispatch. Furthermore, the performance of the closed-loop system is compared with those obtained by implementing a dynamic power dispatch strategy [12] and the DYMONDS approach[31]. We compared our method with the DYMONDS as it is one the most promising methods for solving the economic dispatch problem with distributed predictive features. In order to properly simulate the DYMONDS, we included a ramp-rate constraint in *Problem 1A* of [31] to the initial

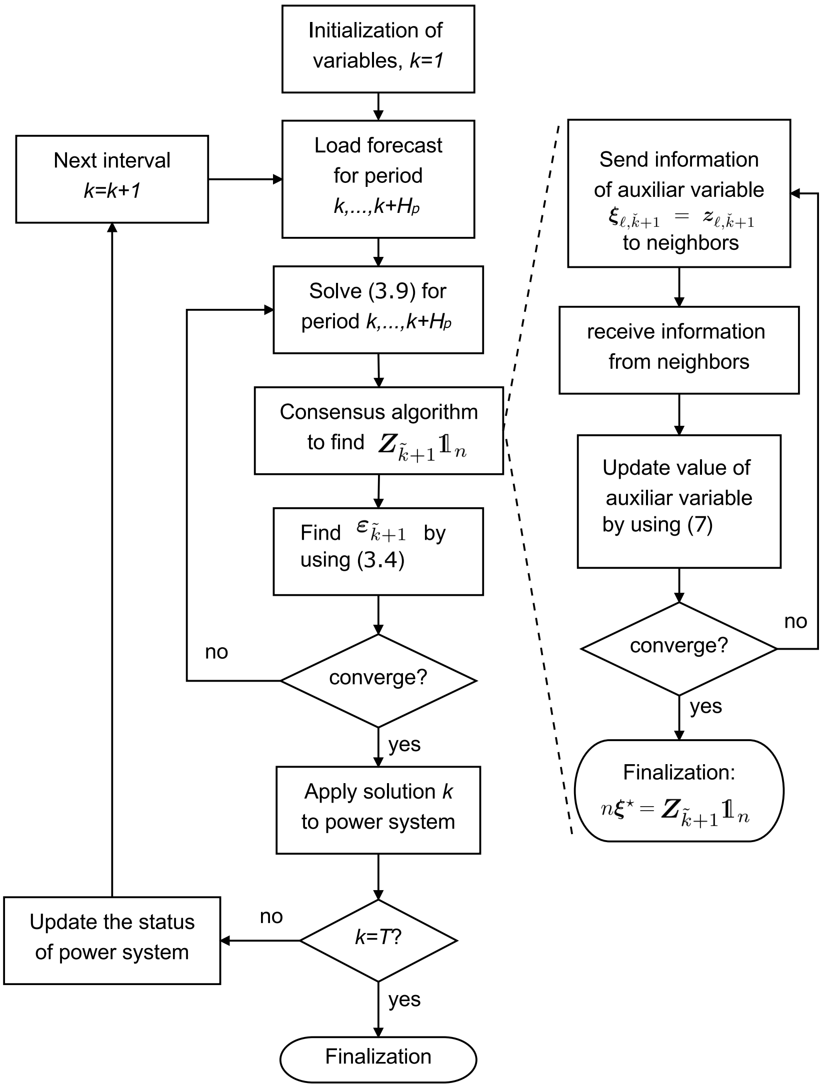


Fig. 3.2 Flow chart of the DDMPC for each generator.

Table 3.1 Parameters of generators in the first simulation case

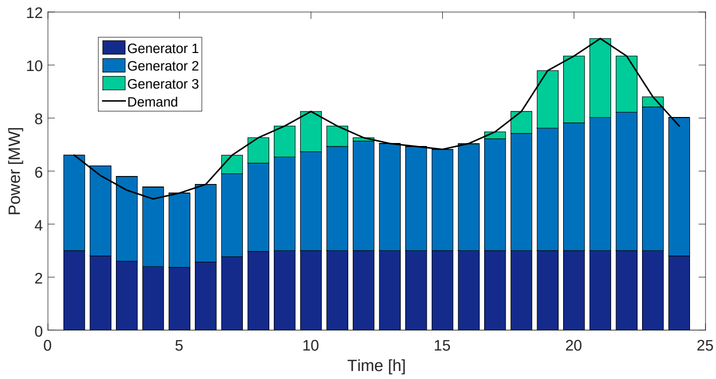
Generator $\ell \in \mathcal{C}$	a_ℓ $[\frac{\$}{\text{MW}^2}]$	b_ℓ $[\frac{\$}{\text{MW}}]$	$P_\ell^{\min}$ [MW]	$P_\ell^{\max}$ [MW]	$\Delta P_\ell^{\min}$ $[\frac{\text{MW}}{\Delta_t}]$	$\Delta P_\ell^{\max}$ $[\frac{\text{MW}}{\Delta_t}]$
1	0.5	1	0	3	-0.2	0.2
2	1	10	0	6	-0.2	0.2
3	2	35	0	4	-4	4

condition, we varied uniformly the price vector by 5% and 40%, and we defined supply functions when the output vector does not change in response to the price variation.

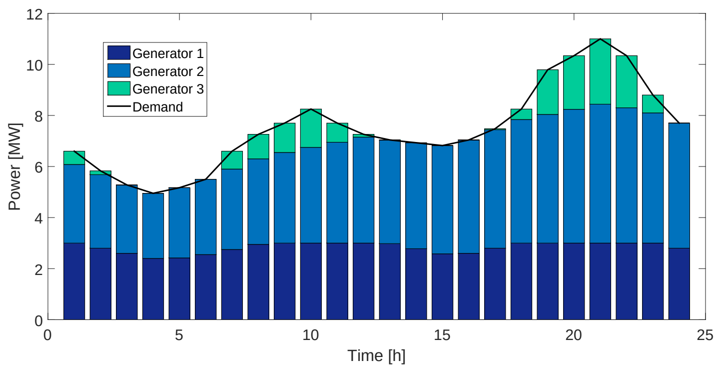
• First scenario: This scenario shows that, under certain circumstances, the traditional dynamic power dispatch is not practically implementable. In particular, the system operation will be exposed to this undesirable condition if there is no UC stage prior to the economic dispatch implementation. In this scenario, the power balance could potentially be violated as ramp-rate constraints are enforced. The generator parameters corresponding to the first scenario are presented in Table 3.1. The marginal costs in this case study are defined for a cheap generator (e.g., hydropower) and thermal plants. The results of the traditional dynamic power dispatch approach and the DDMPC with with a forecast period $H_p = 10$ corresponding to the first scenario are shown in Fig. 3.3(a) and 3.3(b), respectively. Dispatch details of DYMONDS are not shown as they are very similar to the results obtained with the dynamic approach.

Regarding the traditional dynamic power dispatch, this control strategy is not able to satisfy the balance between supply and demand at time instants $k = 2, \dots, 4$, and $k = 24$. The balance is not achieved because this method uploads generator 1 to its capacity so that generator 2 is the marginal unit that supplies the remaining load. However, when the load decreases at the next step, generators 1 and 2 are not capable of decreasing their power generation because of their ramp-rate constraints. The ramping can be adjusted by applying a UC stage prior to the economic dispatch [52]. However, a UC stage increases the computation burden and data requirements to perform the economic dispatch. As in the dynamic dispatch case, the solution of DYMONDS with 5% is not feasible at time instants $k = 2, \dots, 4$, but is feasible at $k = 24$, and the solution of DYMONDS with 40% is always feasible but very expensive (total operation cost is \$3416) as it can be seen in Figs. 4.5(a) and 4.5(b). On the other hand, the use of multi-interval information in the case of DDMPC can provide the required balance (see Fig. 3.3(b)).

In the case of the MPC-based economic dispatch, the balance of supply and demand is achieved for forecast periods $H_p = 2$ and $H_p = 10$. However, the solution performance is better when additional information of load forecast (i.e., $H_p = 10$) is available. Thereby, the DDMPC controller offers an optimal control sequence, which anticipates load changes. The benefit of having a large forecast period holds as long as the load forecast is accurate. Nevertheless, it should be taken into account that the computation burden increases with a larger forecast period since more decision variables must be computed within the control inputs sequence. The effects of forecast period in the closed-loop performance is observed in Figs. 3.4(a) and 3.4(b), where the total operation cost of the DDMPC controller with $H_p = 2$ (i.e., \$2412) is higher than the DDMPC cost with $H_p = 10$ (i.e., \$2350). The obtained incremental cost is for a single day, which will increase as additional days are considered. However, the cost can be reduced as the base generators (generator 1 in $k = 13, \ldots, 17$) can represent the load forecast and ramp-constraints more precisely. In this case, generator 1 decreases its power output so that generator 2 can produce more energy at peak load periods



(a)



(b)

Fig. 3.3 Results of traditional dispatch approaches applied to the first scenario. (a) Dynamic dispatch. (b) DDMPC with $H_p = 10$.

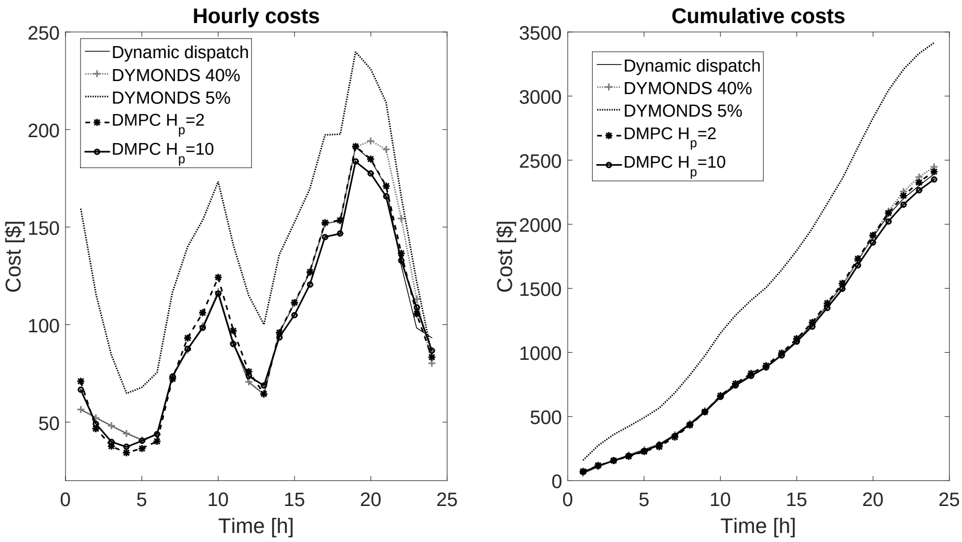
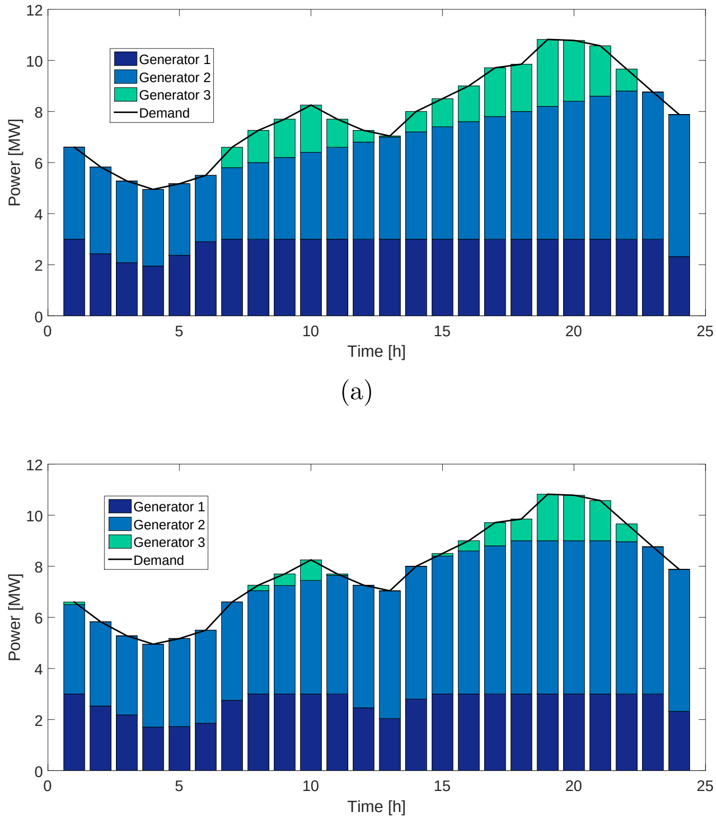


Fig. 3.4 Costs of the first scenario for different alternatives.

(behavior that is not possible to obtain with other control techniques justifying the implementation of predictive strategies).

• Second scenario: This scenario shows that considering multi-interval events could reduce the power system operation costs by applying preventive solutions. Here, generator 1 does not have a ramping-rate constraint and can respond flexibly to load changes, the other parameters remain the same as in the first scenario. When the load increase is larger than the ramping rate of the marginal unit, a more expensive generator must be used, thereby increasing operational costs. However, if such situation can be anticipated, base generators decrease their output for ramp-enforced generators increase their production before load increases. This action minimizes the use of expensive generators when demand rises.

From the previous results it can be seen that the dynamic dispatch and DYMONDS with %40 have lower costs for some hours than those of the DDMPC controller with $H_p = 10$. However, the hourly and cumulative costs of dynamic dispatch, DYMONDS, and DDMPC with $H_p = 10$ in the first scenario are very similar. Nevertheless, the DDMPC dispatch performs much better than the dynamic dispatch and DYMONDS for some specific system conditions (e.g., second scenario). Specifically, consider the results in Fig. 3.5 in which the DDMPC with $H_p = 10$ has reduced the output of generator 1 at $k = 5, \dots, 7$, and $k = 12, \dots, 14$. This preventive action allows generator 2 to increase its production as the system reduces the dispatch of the most expensive generator. The costs shown in Fig. 3.6 demonstrate the hourly as well as the cumulative dispatch costs. The cumulative cost shows that the DDMPC with $H_p = 10$ is better



(a)

(b)

Fig. 3.5 Results of the second scenario. (a) Dynamic dispatch. (b) DDMPC with $H_p = 10$.

than dynamic dispatch and DYMONDS from $k = 7$. In this case, the cumulative cost difference for 24 hours is about \$190 with respect to dynamic dispatch and \$248 with respect to DYMONDS.

In summary, the closed-loop feature allows the DDMPC to update the system performance by considering all available options. Thereby, the DDMPC would be a promising method to address the economic dispatch problem in uncertain conditions with imperfect data. In addition, the MPC-based approach offers additional options for applying the optimization-based method in conjunction with predictive models. Although the MPC is considered a promising alternative for the traditional single-period economic dispatch problem, it relies on an accurate forecast of future system conditions such as the system load and generation of renewable resources. For simplicity, we have assumed that the load forecasts for calculating the MPC-based dispatch are accurate.

3.4.2 DDMPC Computation Performance and Convergence Test

The following simulation case is used to show that the proposed DDMPC achieves a balance of supply and demand as an optimal performance is obtained for the generators. Here, we compare the behavior of DDMPC with those of dynamic power dispatch and a centralized MPC for three time intervals. We used a modified version of the generators and network presented in [31] by changing some generator parameters and maintaining the peak load and the daily load profile for highlighting the MPC abilities. First, the DDMPC is compared with the centralized MPC to verify that it achieves the same efficient behavior while satisfying energy balance. Then, DDMPC is simulated for three different configurations to show that with more information the operator can obtain better solutions. Table 3.2 shows the parameters for five generators with specific technical and economic characteristics.

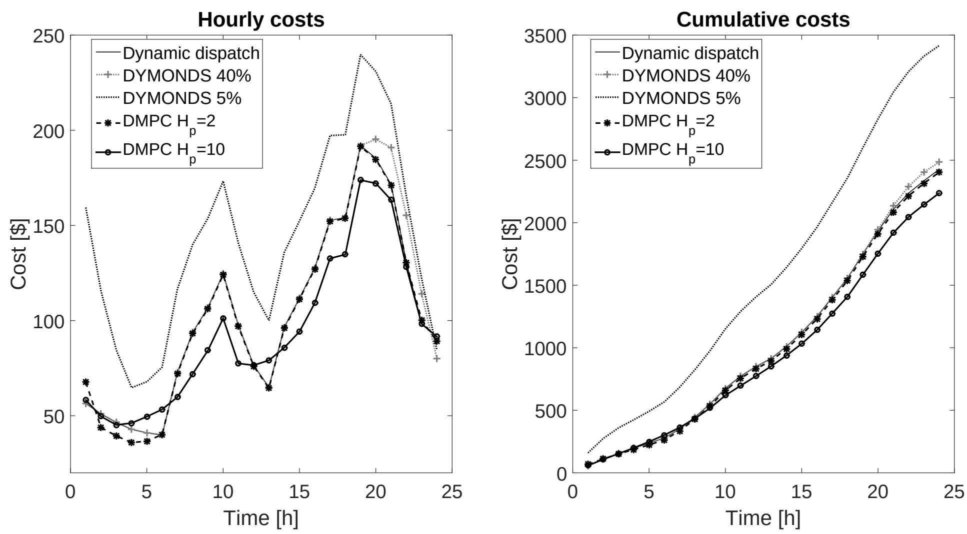
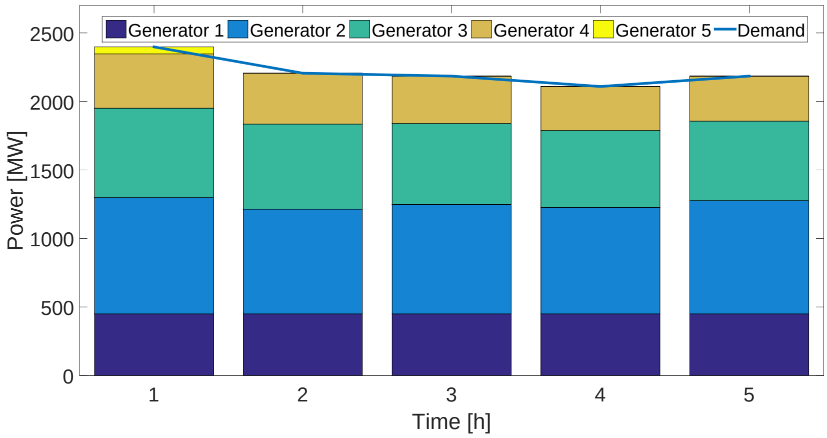


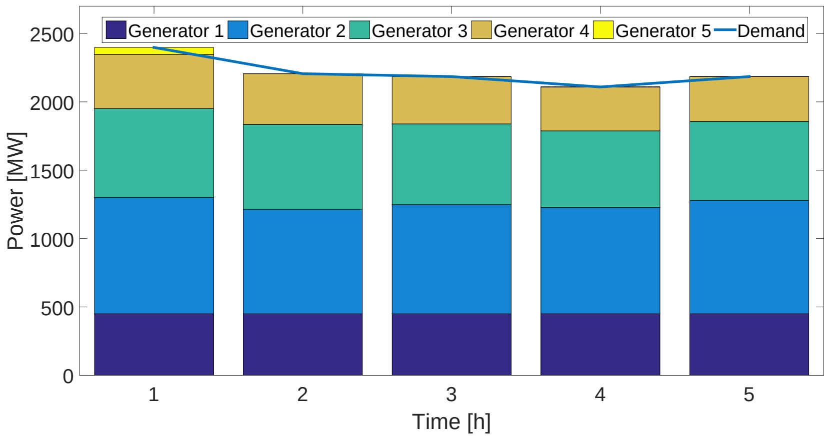
Fig. 3.6 Costs of the second scenario for different alternatives.

Table 3.2 Parameters of generators for the second simulation case

Generator $\ell \in \mathcal{C}$	a_ℓ $[\frac{\$}{\mathrm{MW}^2}]$	b_ℓ $[\frac{\$}{\mathrm{MW}}]$	$P_\ell^{\min}$ [MW]	$P_\ell^{\max}$ [MW]	$\Delta P_\ell^{\min}$ $[\frac{\mathrm{MW}}{\Delta_t}]$	$\Delta P_\ell^{\max}$ $[\frac{\mathrm{MW}}{\Delta_t}]$
1	0	50	0	450	-200	200
2	0	100	0	800	-100	100
3	0	150	0	1000	-30	30
4	0	200	0	800	-25	25
5	0	300	0	800	-800	800



(a)



(b)

Fig. 3.7 Comparison of centralized MPC and DDMPC with five generators. (a) Centralized MPC with $H_p = 2$. (b) DDMPC with $H_p = 2$.

Fig. 3.7 presents an hourly simulation with five generators by using the centralized MPC and the proposed DDMPC. Results show that the solutions obtained by DDMPC and centralized MPC are quite similar as both approaches satisfy all physical and operation constraints in a preventive framework. In addition, it was verified that DDMPC presents the same behavior as the centralized MPC. For such reason, the results of the centralized MPC are not displayed. The convergence analysis of the algorithm is shown in Fig. 3.8 and Fig. 3.9, while results of the dynamic power dispatch and the proposed DDMPC are presented in Figs. 3.10(a), 3.10(b), and Fig. 3.11 for different forecast periods. Since the algorithm proposed to solve the economic dispatch problem is iterative, it is necessary to show that it converges to an efficient solution.

Fig. 3.8 and Fig. 3.9 show the evolution of the Lagrange multiplier associated to energy balance and the evolution of power generated by each power plant at $k = 5$ and $H_p = 2$, respectively. On one hand, at the process beginning the Lagrange multiplier is very volatile, but its volatility decreases when iterations increase. Convergence of the Lagrange multiplier is achieved before 350 iterations. On the other hand, generators' output converge if the energy price is stable. In this case, the output of generators converge before 500 iterations. However, this is not always true since it depends directly on the cost functions of generators. For instance, if there is no quadratic term in the cost function, there will be several dispatch solutions for the same electricity price. This undesirable effect can be mitigated by including a very small (but different from zero) quadratic term in the cost function. In terms of the algorithms performance, detailed results of the economic dispatch are shown in Figs. 3.10(a), 3.10(b), and Fig. 3.11 for different forecast periods. As the dynamic approach does not consider multi-interval events in the objective function, cheaper generators are dispatched up to their capacities and reduce their outputs only when the load drops. In Fig. 3.10(a), the cheapest generators 1, 2, and 3 follow the load reduction at $k = 3, 4, 5, 23, 24$, and generator 4 should be dispatched next when the load increases. However, generator 4 has a ramp-rate limitation. In this case, generator 5 (i.e., the most expensive) must be dispatched to fulfill the hourly load requirements. Again, this shortcoming can be mitigated by using a predictive strategy. Fig. 3.10(b) shows the dispatch results when applying the proposed DDMPC with $H_p = 23$. In contrast to the dynamic

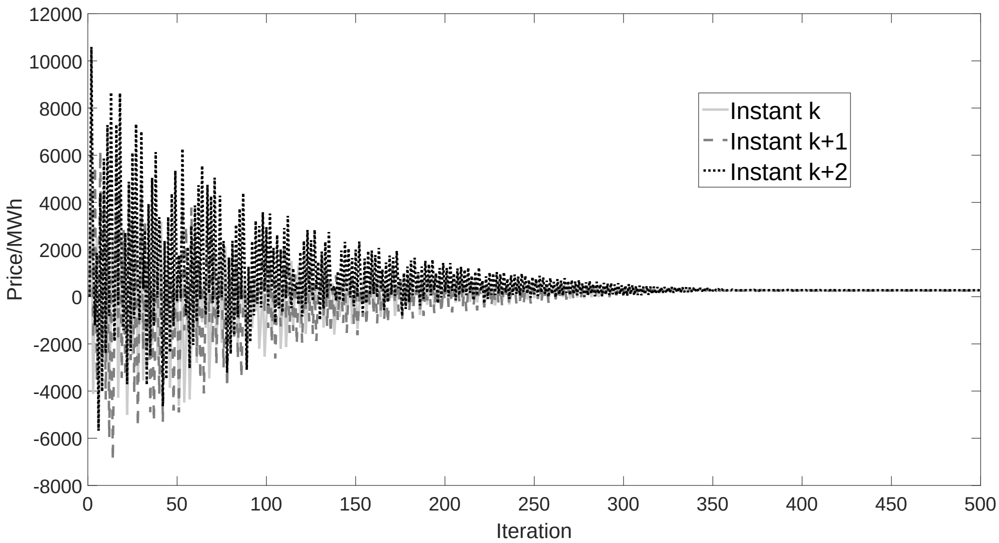


Fig. 3.8 Evolution of Lagrange multiplier for $k = 5$ and $H_p = 2$.

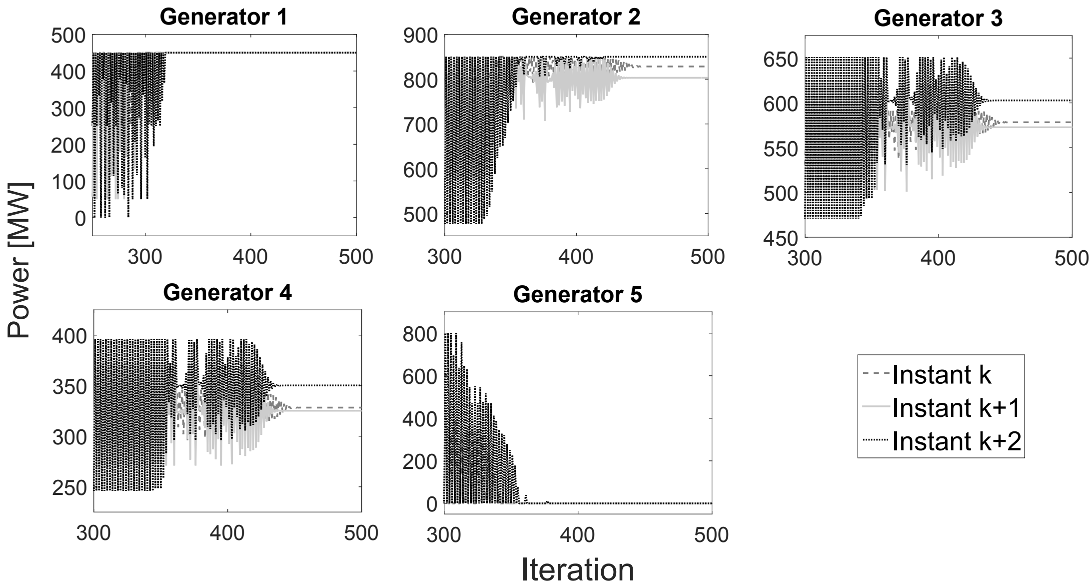


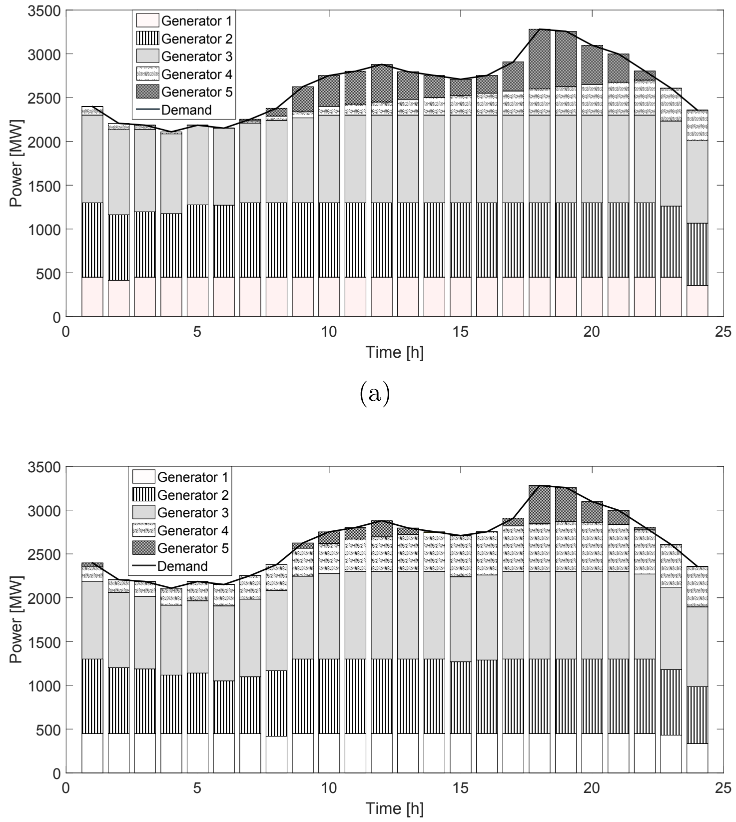
Fig. 3.9 Evolution of generators' power for $k = 5$ and $H_p = 2$.

dispatch, generators 1, 2, and 3 follow the hourly load specifically for $k = 6, 7, 8, 15$ as a preventive strategy to minimize operational costs. Accordingly, generator 4 increases its output from the beginning to satisfy the ramp constraints as the dispatch of generator 5 is significantly reduced.

The DDMPC configuration is modified and tested for a short term DDMPC ($H_p = 5$) and a medium term DDMPC ($H_p = 10$). Fig. 3.11 shows the hourly and cumulative costs for the dynamic dispatch and DDMPC. It can be seen that the DDMPC with $H_p = 23$ presents the best performance and significant costs can be avoided (i.e., \$210,792 per day) by using this solution instead of dynamic dispatch. Indeed, the DDMPC with $H_p = 23$ has the lowest cost in each hour. For the other cases (i.e., $H_p = 5$ and $H_p = 10$), the DDMPC performance is very similar to that of dynamic dispatch. The DDMPC with $H_p = 10$ is less expensive than the dynamic dispatch (i.e., \$19,080 lower) but the DDMPC $H_p = 5$ is more expensive (\$7,090 higher). Accordingly, we verified that the forecast period is an important parameter since it has a direct impact on the minization of operation costs. However, a larger number of forecast periods tends to increase the computation burden as well.

3.5 Concluding Remarks

An MPC-based distributed dispatch has been proposed to find the optimal power outputs of generators to meet a dynamic load. The proposed method manages to



(a)

(b)

Fig. 3.10 Results of the second simulation case. (a) Dynamic dispatch. (b) DDMPC with $H_p = 23$.

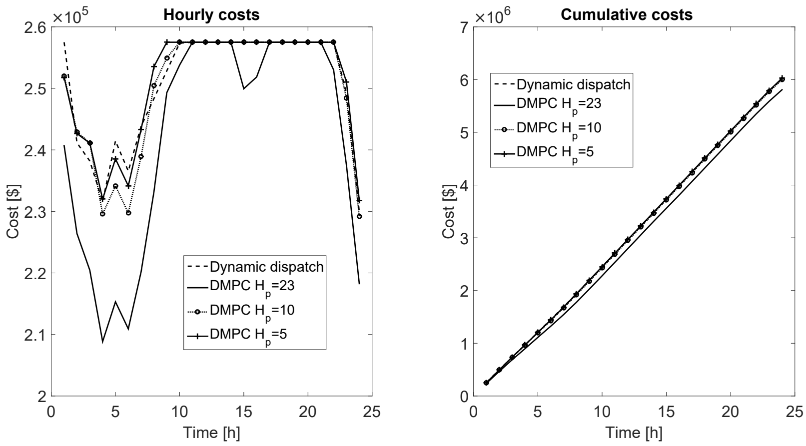


Fig. 3.11 Costs of the second simulation case.

achieve the balance between energy generation and consumption, while minimizing the system's operation costs. That is the main contribution of this chapter, i.e., a method that emulates the centralized dispatch solution in a distrbuted manner. In the proposed method, generators communicate with each other based on a consensus algorithm, without sharing private information such as generation costs and capacities, as another contribution of this chapter.

Although MPC approaches are more commonly applied in industrial applications rather than power systems, the MPC features are promising for the economic dispatch problem, especially for systems in a changing environment. In contrast to other techniques that pre-compute an optimal solution for an operation interval, the MPC finds finite-horizon solutions at runtime. When new information of the system is available, it resolves a new optimization problem by considering forecasted behavior of the system. This characteristic enables the operator to continuously keep tracking of the system and maintain generation dispatch close to an efficient operation point by complying with technical constraints. We verified that the proposed DDMPC performs better than the traditional dynamic dispatch and the promising DYMONDS method, which is also based on MPC.

We are aware that renewable resources are very important in future power systems. Therefore, in the next chapters we to propose a distributed-stochastic MPC for solving the economic dispatch problem. The proposed approach forms the basis of such goal and some additional features are be included.

Chapter 4

Intra-Hour Microgrid Economic Dispatch Based on Model Predictive Control

Renewable energy-based generation facilities emerging in microgrids are modifying many traditional principles of economic dispatch because of the variability and uncertainty of their output characteristics. Since the power generation from renewable resources is difficult to anticipate, a real-time adjustment of generation schedules is necessary after more forecast information becomes available. Intra-hour or ultra-short-term dispatch, allows microgrid operators to frequently update generators' outputs for providing power supplies efficiently in an uncertain operating condition. However, several technical challenges such as information availability, control architecture, and computational burden make it difficult to find an optimal generation schedule at runtime. This work addresses the intra-hour economic dispatch problem by designing a closed-loop distributed model predictive control that reduces potential variations in the determined generation schedules. At first, optimization problems regarding the behaviors of several participants in a microgrid are formulated. Then, the procedures forachieving the real-time power balance under ramp-rate constraints are detailed. Simulation results present the efficiency of the proposed DMPC for the optimal intra-hour economic dispatch when multiple types of generation resources are considered in a microgrid.

4.1 Introduction

In the microgrid operation, the energy demand must be satisfied by finding the optimal generation schedule of available resources with various operation and cost characteristiscs. Towards finding the optimal operation of a microgrid, it is necessary to solve an optimization problem with economic and/or technical criteria including several soft constraints related to generation specifications and a usually hard constraint associated to the balance between production and demand. This process is known as microgrid economic dispatch.

In the last years, there has been a technological breakthrough in the way that electrical energy is produced, and this has increased the amount of renewable energy resources to produce energy. For instance, it is possible to generate electricity from solar radiation, wind speed, tidal force, and so forth. In addition, there are new elements (such as active participation of users through demand response programs, integration of electric vehicles, energy storage systems, and distribution automation) that provides flexibility in power system operations but complicates the power dispatch process. Altogether, these elements can be part of what is known nowadays as a smart grid, and on a smaller scale a microgrid.

The smart grid concept is a new trend in power systems that comprehends and integrates economics, policy and regulation, control and automation, communication systems, grid infrastructure, and technical criteria. This new concept enables a more efficient supply of energy through the active interaction between demand, offer, and the system operator. A smart grid or a microgrid requires a reliable and efficient communication network for sharing intensive data since a central agent receives information from all system participants and determines their best possible behavior in terms of an objective function. The objective function in a centralized approach can be related to global benefit maximization since there is information available from all participants. Although a centralized approach is advantageous in making accurate and comprehensive decisions, its strict communication requirement might represent an obstacle for operating a microgrid with a multitude of control elements that need a large communication bandwidth.

On the contrary, distributed control architectures that involve only local decision variables have simpler communication requirements so that it is not necessary to have a central control agent (e.g., microgrid master controller) nor to establish the associated communication links. However, the design of a distributed control architecture is quite challenging due to the existence of coupling constraints and dynamics that interrelate the decision making of individual controllers. Camponogara et al. and Negenborn et al. ([16] and [49], respectively) presented a discussion regarding the distributed control scheme for implementing model predictive control [45].

As MPC methods have been commonly applied in industrial applications, the interest in applying such methods in power systems is intensified due to integration of renewable energy-based distributed generation technologies. Traditionally, the economic dispatch problem was solved by approaches that compute an optimal solution for a certain time invertal in an off-line open-loop manner. However, with the presence of more disturbances in power system operations due to the stochastic nature of renewable resources, off-line open-loop methods are facing concerns about their efficiency and accuracy. In contrast, MPC methods solve an open-loop finite-horizon control problem based on the current operating state of the system. After new measurements and forecast information of the system are available, a new open-loop finite-horizon optimization problem with updated initial conditions is solved. Accordingly, MPC is known as an on-line closed-loop method that mitigates the issue of variability and uncertainty, and its response to large disturbances is improved when combined with stochastic methods, such as scenario decomposition.

Several authors have worked on MPC methods applied to the economic dispatch problem by considering deterministic and stochastic approaches for centralized and distributed control strategies. In [24], Elaiw et al. proposed an economic dispatch problem by considering emissions constraints. Here, generators can find their optimal energy output by using the profit-based emissions-constrained dynamic economic dispatch. A two-stage stochastic energy management system was proposed by Olivares et al. in [52]. In the first stage the authors solve a stochastic UC, and in the second stage they solve a shrinked horizon optimal power flow to deal with network constraints. Mayhorn et al. in [44] used MPC to manage diesel generators and energy storage to integrate wind power plants. The authors minimize fuel costs and maximize wind generation. Xia et al. in [70]. showed that MPC is suitable to solve dynamic economic dispatch problems. The authors found some advantages of MPC in comparison to an optimal control approach, and explored robust MPC. In [78], Zhu et al. proposed a switched MPC model that deals with the management of energy storage in a photovoltaic system. They used switched constraints instead of a switched state space model. An energy management model that finds optimal charging and discharging periods for a battery in the presence of wind energy was proposed by Prodan et al. in [55]. This energy management system minimizes power imported from the grid, and encourages utilization of wind power plants and the battery system during peak load. In [63], Torreglosa et al. presented an energy dispatch based on MPC for an off-grid hybrid system with hydrogen storage. Their MPC finds the optimal power to be delivered or absorbed by the hydrogen system per each hour by considering power limitations of controlled sources. Ilić et al. in [31] proposed a method known as DYMONDS, which has both centralized and distributed features. They showed that a fully distributed algorithm without an explicit balance constraint does not reach balance between generation and demand. In addition, these authors applied MPC to solve an economic and environmental dispatch with intermittent resources in [72]. A rule-based MPC model to manage battery charging and discharging was proposed by Liu et al. in [41]. The algorithm is an energy management system that considers PV integration. Del Real et al. in [2] designed a distributed MPC based on Lagrange-MPC. The proposed optimization problem minimizes both economic and environmental costs in energy hubs (with generation and demand) that are interconnected.

To the best of our knowledge, there is a lack of research on distributed MPC for the ultra-short term economic dispatch with ramp-rate constraints. A key topic to investigate is achieving balance between energy and demand in a distributed approach without requiring the intervention and optimization of a central controller. As it has been shown by Ilić et al. [31], a fully-distributed approach without a coupling balance constraint will deviate from an appropriate operation point. Moreover, an approach with a coupling balance constraint proposed in [66] yields a very good performance as it obtains the same solution as a centralized approach, but might not be feasible for the very short-term economic dispatch because of its decision variables amount and computational burden. In this research, we provide a distributed MPC (DMPC) for the ultra-short term economic dispatch problem by considering ramp-rate constraints and energy balance. Energy balance is not considered explicitly as a coupled constraint. Instead, balance is reached through energy price and several algorithms proposed in this chapter. In this chapter, the role of the grid operator is to participate in data treatment and acquisition, especially for determining the energy price. That is, centralized optimization is avoided.

The remainder of this chapter is organized as follows. In Section 4.2 the background of MPC, consensus algorithm, problem statement, and distributed model predictive control is provided. Section 4.3 describes the formulation for different participants in a microgrid. In Section 4.4 the DMPC is explained in detail. The case study and results are presented in Section 4.5. Finally, in Section 4.6 conclusions are drawn.

4.2 Mathematical Background

To describe the economic dispatch problem consider m generators from the set $\mathcal{N} = \{1, \ldots, m\}$, with limits stated as $P_v^{\min}$ and $P_v^{\max}$, ramp restrictions of $\Delta P_v^{\min}$ and $\Delta P_v^{\max}$, and a generation cost function given as $C_v(P_{v,k}) = a_v P_{v,k}^2 + b_v P_{v,k}$, where $v = 1, \ldots, m$. Given the set of generators $\mathcal{N}$, in a centralized approach the system operator determines the scheduling of generators that can meet the time-variant load Q at every time step. In a different research, we proposed a distributed dual-decomposition model predictive control (DDMPC) to solve the centralized economic dispatch problem in a distributed manner [66]. Although the DDMPC is feasible for the hourly economic dispatch, it might not be sufficient to deal with the intra-hour economic dispatch because of its computational burden. For solving such optimization problem in a faster distributed approach, we use the MPC method and the average consensus algorithm that are described as follows:

4.2.1 Average consensus algorithm

Without loss of generality (any set of generators can be used instead of $\mathcal{N}$), consider a connected undirected graph denoted by $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where each node in the set $\mathcal{N}$ is associated with a decision variable denoted by P_v. According to the graph theory, if information from every node is collected by a central agent that makes all the decisions, then the control architecture is centralized. Alternatively, given an optimization problem with a specific data structure, it is possible to solve the problem in a distributed manner. We propose in this chapter an algorithm that determines the summation of outputs from different agents without the need of acquiring individuals' information. The main idea is to compute the summation in the form $\sum_{v \in \mathcal{N}} P_{v,\tilde{k}}$ in a distributed manner as an additional step during the execution of MPC. More specifically, the following process is performed. Let $\boldsymbol{\xi} \in \mathbb{R}^m$ be a vector of auxiliary variables, i.e., $\xi_v \in \mathbb{R}$ corresponding to a node $v \in \mathcal{N}$. The variables are initialized with the current values of decision variables, i.e., $\xi_{v,0} = P_{v,\tilde{k}}$, for all $v \in \mathcal{N}$. Therefore, a continuous-time standard average consensus algorithm is computed, i.e.,

$$\xi_{v,\check{k}+1} = \xi_{v,\check{k}} + \sum_{i \in \mathcal{N}_v} w_{vi} \left(\xi_{i,\check{k}} - \xi_{v,\check{k}} \right), \quad \forall v \in \mathcal{N} \tag{4.1}$$

where w_{vi} is the weight of the link between nodes v and i. Since the graph is undirected, $w_{vi} = w_{iv}$. Here, $\check{k}$ is the discrete time for a sampling time very close to zero. If the communication graph $\mathcal{G}$ is connected and the weight of links are symmetrical, then the dynamics in (4.1) converge to $\boldsymbol{\xi}^\star \in \mathbb{R}^m$, where $\xi_v^\star = \sum_{v\in\mathcal{N}} \xi_{v,0}/|\mathcal{N}|$, for all $v \in \mathcal{N}$ [51]. Accordingly,

$$|\mathcal{N}|\xi_v^\star = \sum_{v\in\mathcal{N}} P_{v,\tilde{k}}, \quad \forall\, v \in \mathcal{N},$$

Hence, each node in the graph shares data with its neighbors so as to find $\sum_{v\in\mathcal{N}} P_{v,\tilde{k}}$ in a distributed manner. In addition, the average consensus algorithm can be used for spreading data in the set as follows. Consider that $\vartheta_{\tilde{k}}$ is the information to be spread and that $\mathcal{N}$ is divided into the set of nodes $\mathcal{N}^{\mathrm{com}}$ and $\mathcal{N}^{\mathrm{unc}}$. The set $\mathcal{N}^{\mathrm{com}}$ is in direct communication with the information to be spread, whereas $\mathcal{N}^{\mathrm{unc}}$ lacks this communication. For spreading data, the auxiliary variables are initialized as follows: $\xi_{v,0} = \vartheta_{\tilde{k}}$, for all $v \in \mathcal{N}^{\mathrm{com}}$, and $\xi_{v,0} = 0$, for all $v \in \mathcal{N}^{\mathrm{unc}}$. Therefore, the average consensus algorithm leads to a converged solution like (4.1). Finally, a node in the set $\mathcal{N}^{\mathrm{unc}}$ computes $\vartheta_{\tilde{k}}$ as

$$\frac{|\mathcal{N}|}{|\mathcal{N}^{\mathrm{com}}|}\xi_v^\star = \vartheta_{\tilde{k}}, \quad \forall\, v \in \mathcal{N}^{\mathrm{unc}}.$$

4.3 Formulation of Microgrid Participants

In order to solve the economic dispatch problem with a fully distributed approach, we propose the following formulation for a microgrid where the participants maximize their benefits as balance is achieved. Here, four types of participants are considered: conventional generators, stand-alone energy storage systems, renewable energy-based generators, and renewable energy-based generators with ESS. On the one hand, the problem formulation proposed for conventional generators is different from the DDMPC proposed in [66]. The differences contribute to reduce the computational time so as to solve the intra-hour economic dispatch in an online fashion. On the other hand, the other three types of participants are included as they are important generation resources in a microgrid. Note that in this chapter $\mathcal{N} = \mathcal{C} \cup \mathcal{B} \cup \mathcal{M} \cup \mathcal{U}$ as we consider four types of participants. The problem formulation that facilitates distributed optimization for each type of participants is discussed as follows.

4.3.1 Conventional generators

Conventional generators (e.g., thermal and hydropower generators) have two characteristics: i) they have a firm input whose flux can be easily determined and adjusted, and ii) their generation costs are characterized by a second order function $C_\ell(P_{\ell,k}) = a_\ell P_{\ell,k}^2 + b_\ell P_{\ell,k}$. The optimization problem for dispatching a conventional generator is to maximize the net benefit, which is formulated as:

$$\underset{P_{\ell,k+j|k}}{\text{maximize}} \sum_{j=0}^{H_p} \Big(\pi_{k+j} P_{\ell,k+j|k} - C_\ell(P_{\ell,k+j|k})\Big), \tag{4.2a}$$

subject to

$$P^{\min}_{\ell,k+j} \leq P_{\ell,k+j|k} \leq P^{\max}_{\ell,k+j}, \tag{4.2b}$$

$$\Delta P^{\min}_{\ell,k+j} \leq \Delta P_{\ell,k+j|k} \leq \Delta P^{\max}_{\ell,k+j}. \tag{4.2c}$$

Note that this optimization problem does not include an explicit constraint of energy balance. Instead, the balance is automatically achieved through the price signal that is determined by the microgrid operator. The operator receives and integrates the bids of generation quantities and prices, then constructs the marginal cost function of the microgrid under various load levels

We assume that bidding prices of all generators reflect exactly their marginal costs so that the electricity price equals the marginal cost of at least one generator $\ell \in \mathcal{C}$. Such assumption holds in a competitive market [38] as well as in a microgrid comprising renewable energy generation with low marginal costs. Accordingly, conventional generators are the only participants that dominate the price formation.

Definition 1. Power balance is achieved in (4.2a) as long as $\pi_{k+j} = \frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}}$ holds for all $\ell \in \mathcal{C}$, $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$ when $C_\ell(P^{\min}_{\ell,k+j}) \leq \pi_{k+j} P_{\ell,k+j|k} \leq C_\ell(P^{\max}_{\ell,k+j})$. In addition, $P_{\ell,k+j|k} = P^{\min}_{\ell,k+j}$ if $\pi_{k+j} < \frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}}|_{P_{\ell,k+j|k}=P^{\min}_{\ell,k+j}}$, and $P_{\ell,k+j|k} = P^{\max}_{\ell,k+j}$ if $\frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}}|_{P_{\ell,k+j|k}=P^{\max}_{\ell,k+j}} < \pi_{k+j}$.

The first-order optimality condition of (4.2a) implies that

$$\sum_{j=0}^{H_p} \pi_{k+j} = \sum_{j=0}^{H_p} \frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}}, \tag{4.3}$$

several optimal but non-implementable solutions can be found since not necessarily $\pi_{k+j} = \frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}}$ for all $\ell \in \mathcal{C}$, $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$, i.e., Definition 1 is not satisfied. To solve this issue, the economic dispatch described in (4.2a) is modified, but maintaining the main goal of benefits maximization. From the first order condition (4.3), now we want to

$$\underset{P_{\ell,k+j|k}}{\text{minimize}} \sum_{j=0}^{H_p} \left\| \pi_{k+j} - \frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}} \right\|^2 \tag{4.4}$$

subject to (4.2b) and (4.2c). The proposed objective function represents the deviation from the desired equality $\pi_{k+j} = \frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}}$ for all $\ell \in \mathcal{C}$, $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$, and meets the first order condition of (4.2a) in its optimal. If generators are not enforced by ramping limitations, the economic dispatch (4.4) maximizes the net benefit of generators whereas balance between demand and supply is maintained. Nevertheless, the balance might not be possible in the presence of an active ramp-rate constraint as marginal production costs are not equal to the vector of energy price.

First, let us analyze the problem posed in (4.4), which is the optimization problem solved by conventional generators without any ramps correction. This problem yields balance if the ramps are not enforced with the initial condition. However, balance can be infringed if ramps are enforced. Without loss of generality, this issue can be observed by expanding (4.4) for $H_p = 1$:

$$\underset{P_{\ell,k+j|k}}{\text{minimize}} \left\| \pi_k - \frac{\partial C_\ell(P_{\ell,k|k})}{\partial P_{\ell,k|k}} \right\|^2 + \left\| \pi_{k+1} - \frac{\partial C_\ell(P_{\ell,k+1|k})}{\partial P_{\ell,k+1|k}} \right\|^2 \tag{4.5}$$

Definition 2. Since the theoretic optimal value of (4.5) is zero, it is desired that $P_{\ell,k|k} = \frac{\pi_k - b_\ell}{2a_\ell}$ and $P_{\ell,k+1|k} = \frac{\pi_{k+1} - b_\ell}{2a_\ell}$.

Definition 3. The economic dispatch must comply with security constraints, that is, the following condition must be respected: $\frac{\partial C_\ell(P_{\ell,k|k})}{\partial P_{\ell,k|k}} \leq \pi_k$ and $\frac{\partial C_\ell(P_{\ell,k+1|k})}{\partial P_{\ell,k+1|k}} \leq \pi_{k+1}$.

Proposition 1. *The ramp of generator ℓ is enforced if $\pi_{k+1} - \pi_k < 2a_\ell \Delta P^{min}$ or $\pi_{k+1} - \pi_k > 2a_\ell \Delta P^{max}_{\ell,k+1}$.*

Proof. Let $\pi_{k+1} = 2a_\ell \Delta P^{\max}_{\ell,k+1} + \pi_k + \eta$, where $\eta > 0$. From Definition 1 and Definition 2, the desired generation at k is $\tilde{P}_{\ell,k|k} = \frac{\pi_k - b_\ell}{2a_\ell}$ and the desired generation at $k+1$ is $\tilde{P}_{\ell,k+1|k} = \frac{\pi_{k+1} - b_\ell}{2a\ell} = \Delta P^{\max}_{\ell,k+1} + \tilde{P}_{\ell,k|k} + \frac{\eta}{2a_\ell}$. Then, $\tilde{P}_{\ell,k+1|k} - \tilde{P}_{\ell,k|k} = \Delta P^{\max}_{\ell,k+1} + \frac{\eta}{2a_\ell} > \Delta P^{\max}_{\ell,k+1}$. $\square$

The same procedure can be used to proof Proposition 1 when $\pi_{k+1} < \pi_k$. In a feasible and secure dispatch the maximum admissible generation value at $k+1$ when ramp is enforced is $P_{\ell,k+1|k} = \frac{\pi_k - b_\ell}{2a_\ell} + \Delta P^{\max}_{\ell,k+1}$ if $\pi_{k+1} = 2a_\ell \Delta P^{\max}_{\ell,k+1} + \pi_k + \eta$, and $P_{\ell,k+1} = \frac{\pi_k - b_\ell}{2a_\ell} + \Delta P^{\min}_{\ell,k+1}$ if $\pi_{k+1} = 2a_\ell \Delta P^{\min}_{\ell,k+1} + \pi_k - \eta$. Nevertheless, such feasible solution cannot be obtained by solving (4.5).

Proposition 2. *A non-secure and non-feasible dispatch of generator ℓ, such that $\frac{\partial C_\ell(P^\star_{\ell,k|k})}{\partial P^\star_{\ell,k|k}} > \pi_k$, is the optimal solution of* (4.5) *when ramps are enforced and $\pi_k < \pi_{k+1}$, and it is given by $P^\star_{\ell,k|k} = \frac{\pi_k - b_\ell}{2a_\ell} + \frac{\eta}{4a_\ell}$.*

Proof. Let $\pi_{k+1} = 2a_\ell \Delta P^{\max}_{\ell,k+1} + \pi_k + \eta$, where $\eta > 0$, and $P_{\ell,k|k} = \frac{\pi_k - b_\ell}{2a_\ell} + \gamma$, where $\gamma \geq 0$. By using Definition 1 and Proposition 1, we know that the desired generation at $k+1$ is $\tilde{P}_{\ell,k+1|k} = \Delta P^{\max}_{\ell,k+1} + \tilde{P}_{k|k} + \frac{\eta}{2a_\ell}$. Then, by complying with the ramp constraint we have that $P_{\ell,k+1|k} = \frac{\pi_k - b_\ell}{2a_\ell} + \gamma + \Delta P^{\max}_{\ell,k+1} \leq \tilde{P}_{\ell,k+1|k}$, i.e., $0 \leq \gamma \leq \frac{\eta}{2a_\ell}$. Replacing marginal cost functions in (4.5) we have that the objective function is $8a_\ell^2\gamma^2 + \eta^2 - 4a_\ell\eta\gamma$. The first derivate of this function equals zero when $\gamma = \frac{\eta}{4a_\ell}$, i.e., it is the minimum as the second derivate is positive. Then, the optimal generation at k is $P^\star_{\ell,k|k} = \frac{\pi_k - b_\ell}{2a_\ell} + \frac{\eta}{4a_\ell}$, and at $k+1$ is $P^\star_{\ell,k+1|k} = \frac{\pi_k - b_\ell}{2a_\ell} + \frac{\eta}{4a_\ell} + \Delta P^{\max}_{\ell,k+1} \leq \tilde{P}_{\ell,k+1|k}$. □

From the same analysis of Proposition 2, it is straightforward to show that when ramps are enforced and $\pi_{k+1} \leq \pi_k$, the optimal generation at k is $P^\star_{\ell,k|k} = \frac{\pi_{k+1} - b_\ell}{2a_\ell} + \frac{\eta}{4a_\ell} - \Delta P^{\min}_{\ell,k+1}$, and at $k+1$ is $P^\star_{\ell,k+1|k} = \frac{\pi_{k+1} - b_\ell}{2a_\ell} + \frac{\eta}{4a_\ell}$.

To remediate this issue, consider the following optimization problem that solves each generator by including an auxiliary variable Ψ to (4.4).

$$\underset{P_{\ell,k+j|k}}{\text{minimize}} \sum_{j=0}^{H_p} \left\| \pi_{k+j} - \frac{\partial C_\ell(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}} - \Psi_{\ell,k+j} \right\|^2, \tag{4.6}$$

subject to (4.2b) and (4.2c). The proposed formulation is equivalent to the DDMPC proposed in [66], with the same structure. Here, the auxiliary variable represents a component of the marginal cost of the energy that should be delivered by the generator under ideal conditions, i.e., without constraints. This auxiliary variable allows us to reach the balance between demand and generation even in the presence of ramp rate constraints.

4.3.2 Stand-alone ESS

This element has a very important feature, it can behave as either a generator or a load. This agent chooses to buy from or sell energy to the microgrid market under given price signals so as to conduct arbitrage. As a result, a stand-alone ESS plays a role in peak shifting since it is presumable that it charges when the price is low (i.e., valley load periods) and discharges when the price is high (i.e., peak load periods). Accordingly, we propose the following optimization problem for a stand-alone ESS:

$$\underset{P_{b,k+j|k}}{\text{maximize}} \sum_{j=0}^{H_p} \Big(\pi_{k+j} P_{b,k+j|k} - C_b(P_{b,k+j|k}) \Big), \tag{4.7a}$$

subject to

$$P_{b,k+j}^{\min} \leq P_{b,k+j|k} \leq P_{b,k+j}^{\max}, \tag{4.7b}$$
$$SOC_b^{\min} \leq SOC_{b,k+j|k} \leq SOC_b^{\max}, \tag{4.7c}$$

where $P_{b,k+j|k}$ is the power delivered or stored by the ESS $b \in \mathcal{B}$ at time instant $k+j$, if $P_{b,k+j|k} < 0$ the ESS is charging and buying energy with price π_{k+j}, if $P_{b,k+j|k} > 0$ the ESS is discharging and selling energy with price π_{k+j}. $SOC_{b,k+j|k} = SOC_{b,k+j-1|k} - P_{b,k+j|k}/P_b^{\text{cap}}$. Even though power balance is not included in the above formulation, it can be achieved by deploying local ESS controllers that detect and correct power imbalance in the microgrid [53].

4.3.3 Renewable energy-based generators

This kind of generators have very important features that must be included in the optimization problem. First, the availability of renewable resources (such as wind and solar radiation) is random and not easily predictable. Second, renewable resources cannot be stored unless they have been converted to electricity stored in an ESS. Third, their operational costs are significantly lower than those of conventional generators so that renewable power plants are dispatched as base generators. Accordingly, renewable energy-based generators aim to maximize the net benefit while minimizing the energy deviation from an auxiliary demand $\tilde{D}$ for renewable generation. The auxiliary demand allows us to balance the system when available renewable resources are sufficient to meet the system demand. The corresponding optimization problem is formulated as follows:

$$\underset{P_{r,k+j|k}}{\text{maximize}} \sum_{j=0}^{H_p} \left(\pi_{k+j} P_{r,k+j|k} - C_r(P_{r,k+j|k}) \right), \tag{4.8a}$$

subject to

$$\hat{P}_{r,k+j}^{\min} \leq P_{r,k+j|k} \leq \hat{P}_{r,k+j}^{\max}, \tag{4.8b}$$
$$\Delta P_{r,k+j}^{\min} \leq \Delta P_{r,k+j|k} \leq \Delta P_{r,k+j}^{\max}, \tag{4.8c}$$
$$P_{r,k+j|k} \leq \frac{\tilde{D}_{k+j}}{n_r} \tag{4.8d}$$

Constraint (4.8d) allows us to balance generation and demand when energy demand can be supplied without using conventional generators. Estimated minimum and maximum potential generation are given by the forecasted renewable energy generation.

Real-time power balance is explicitly included in the optimization problem since it is possible that renewable energy generation exceeds the total demand in the microgrid.

4.3.4 Renewable energy-based generators with ESS

Although a renewable energy based generator together with an ESS is more expensive than other solutions, this generation mix enhances the utilization of renewables. The ESS enables the storage of energy from renewable resources when the microgrid load is lower than the available generation of renewable sources or to output stored energy when the microgrid requires additional power injection or the selling price is higher than the purchasing price. The following formulation describes the aforementioned behavior of the generation mix:

$$\underset{P^r_{u,k+j|k},P^b_{u,k+j|k}}{\text{maximize}} \sum_{j=0}^{H_p} (\pi_{k+j}(P^r_{u,k+j|k} + P^b_{u,k+j|k}) - C_u(P^r_{u,k+j|k}, P^b_{u,k+j|k})), \tag{4.9a}$$

subject to

$$\hat{P}^{r,\min}_{u,k+j} \leq P^r_{u,k+j|k} \leq \hat{P}^{r,\max}_{u,k+j}, \tag{4.9b}$$

$$\Delta P^{r,\min}_{u,k+j} \leq \Delta P^r_{u,k+j|k} \leq \Delta P^{r,\max}_{u,k+j}, \tag{4.9c}$$

$$P^{b,\min}_{u,k+j} \leq P^b_{u,k+j|k} \leq P^{b,\max}_{u,k+j}, \tag{4.9d}$$

$$SOC^{\min}_u \leq SOC_{u,k+j|k} \leq SOC^{\max}_u, \tag{4.9e}$$

$$P^r_{u,k+j|k} + P^b_{u,k+j|k} \leq \frac{\tilde{D}_{k+j}}{n_r} \tag{4.9f}$$

4.4 Distributed MPC

In this section we propose an iterative algorithm for solving the economic dispatch in a distributed manner based on the optimization problems stated in section 4.3. To do so, we must define the roles of four groups of participants in the microgrid economic dispatch. First, conventional generators participate directly in the price formation, and inform the microgrid operator their bids along with their available capacity. Second, ESS must inform their neighbors the amount of energy to be delivered to or demanded from the microgrid and keep their decisions even if the energy price changes. This group participates indirectly in the price formation through arbitrage. Third, renewable energy based generators must share information of the expected

Algorithm 1: Iterative DMPC

Variables initialization and set-up of optimization parameters
for $k = 1$ *to operation horizon* **do**
  - initial conditions and estimations of central operator
  for $\tilde{k} = 1$ *to iterations* **do**
    In parallel 1), 2), 3), and 4)
    1) Conventional generators, for all $\ell \in \mathcal{C}$
    - Obtain prices $\boldsymbol{\pi}_{\tilde{k}}$ through consensus algorithm.
    - Find auxiliary balancing signals $\boldsymbol{\Psi}_{\ell,\tilde{k}}$ through Algorithm 7
    - Solve the optimization problem (4.6).
    - Find hypothetical optimal generation without constraints, given by:
    $\tilde{\boldsymbol{q}}_{\ell,\tilde{k}} = \max\left(\frac{\boldsymbol{\pi}_{\tilde{k}} - b_\ell}{2a_\ell}, 0\right).$
    - Verification of active constraints: Algorithm 2 and Algorithm 3.
    - Ramps correction: Algorithm 4 and Algorithm 5.
    - Send generation limits and flags to central controller.
    2) Energy storage systems, for all $b \in \mathcal{B}$
    - Obtain prices $\boldsymbol{\pi}_{\tilde{k}}$ through consensus algorithm.
    - Solve the optimization problem (4.7a).
    - Find through consensus the sum of power from ESS $\boldsymbol{E}_{\tilde{k}} = \sum_{b\in\mathcal{B}} \boldsymbol{P}_{b,\tilde{k}}$.
    3) Renewable generators, for all $r \in \mathcal{M}$
    - Obtain prices $\boldsymbol{\pi}_{\tilde{k}}$ and auxiliary load profile $\tilde{\boldsymbol{D}}_{\tilde{k}}$ through consensus algorithm.
    - Solve the optimization problem (4.8a).
    - Find through consensus the sum of power from renewables
    $\boldsymbol{R}_{\tilde{k}} = \sum_{r\in\mathcal{M}} \boldsymbol{P}_{r,\tilde{k}} + \sum_{u\in\mathcal{U}} \boldsymbol{P}_{u,\tilde{k}}$,
    where $\boldsymbol{P}_{u,\tilde{k}} = \boldsymbol{P}^r_{u,\tilde{k}} + \boldsymbol{P}^b_{u,\tilde{k}}$
    4) Renewable generators with ESS, for all $u \in \mathcal{U}$
    - Obtain prices $\boldsymbol{\pi}_{\tilde{k}}$ and auxiliary load profile $\tilde{\boldsymbol{D}}_{\tilde{k}}$ through consensus algorithm.
    - Solve the optimization problem (4.9a).
    - Find through consensus the sum of power from renewables
    $\boldsymbol{R}_{\tilde{k}} = \sum_{r\in\mathcal{M}} \boldsymbol{P}_{r,\tilde{k}} + \sum_{u\in\mathcal{U}} \boldsymbol{P}_{u,\tilde{k}}$,
    where $\boldsymbol{P}_{u,\tilde{k}} = \boldsymbol{P}^r_{u,\tilde{k}} + \boldsymbol{P}^b_{u,\tilde{k}}$
    Central operator, for all $j \in [0, H_p] \cap \mathbb{Z}_{\geq 0}$
    - Updates demand for conventional generators: $\hat{\boldsymbol{D}}_{\tilde{k}+1} = \hat{\boldsymbol{D}}_0 - \boldsymbol{E}_{\tilde{k}} - \boldsymbol{R}_{\tilde{k}}$
    - Updates auxiliary demand for renewables:
    $\tilde{\boldsymbol{D}}_{\tilde{k}+1} = \hat{\boldsymbol{D}}_0 - \boldsymbol{E}_{\tilde{k}} + \max(\boldsymbol{\Delta}^{\boldsymbol{R}}_{\tilde{k}}, 0)$
    $\boldsymbol{\Delta}^{\boldsymbol{R}}_{\tilde{k}+1} = \boldsymbol{\Delta}^{\boldsymbol{R}}_{\tilde{k}} + \hat{\boldsymbol{D}}_0 - \boldsymbol{E}_{\tilde{k}-1} - \boldsymbol{R}_{\tilde{k}}$
    - Determine prices $\boldsymbol{\pi}_{\tilde{k}+1}$ through Algorithm 6
  end
  - Apply the first optimal control signal for each generator and obtain feedback from the real system for the interval k
end

energy output with neighbors. Because of their generation characteristics, they are preferred over conventional generators for supplying the base load. Fourth, the generation mix of renewable energy based generators and ESS combine the features of the previous two. Finally, the microgrid operator must update both the system demand and the electricity price based on the available information reported by these groups.

Algorithm 2: Analysis of ramp-up active constraint

Inputs: $H_p, P^*_{\ell,k-1}$, and $\tilde{\boldsymbol{q}}_{\ell,\tilde{k}}$
Outputs: $\boldsymbol{r}^{\mathrm{up}}_{\ell,\tilde{k}}$
for $j = 0$ *to* H_p **do**
  $r^{\mathrm{up}}_{\ell,j} = 0$
  if j=0 **then**
    if $\tilde{q}_{\ell,j} - P^*_{\ell,k-1} \geq \Delta P^{\max}_{\ell,k+j} - \epsilon$ ***and*** $P^*_{\ell,k-1} \leq P^{\max}_{\ell,k+j} - \Delta P^{\max}_{\ell,k+j}$ **then**
      $r^{\mathrm{up}}_{\ell,j} = 1$
    end
  else
    if $\tilde{q}_{\ell,j} - \tilde{q}_{\ell,j-1} \geq \Delta P^{\max}_{\ell,k+j} - \epsilon$ ***and*** $\tilde{q}_{\ell,j-1} \leq P^{\max}_{\ell,k+j}$ **then**
      $r^{\mathrm{up}}_{\ell,j} = 1$
    else if $\tilde{q}_{\ell,j} \geq P^{\max}_{\ell,k+j} - \epsilon$ ***and*** $r^{up}_{\ell,j-1} = 1$ **then**
      $r^{\mathrm{up}}_{\ell,j} = 1$
    end
  end
end

Algorithm 3: Analysis of ramp-down active constraint

Inputs: H_p and $\tilde{\boldsymbol{q}}_{\ell,\tilde{k}}$
Outputs: $\boldsymbol{r}^{\mathrm{down}}_{\ell,\tilde{k}}$
$j = H_p$
while $j \geq 1$ **do**
  $r^{\mathrm{down}}_{\ell,j} = 0$
  if $j < H_p$ **then**
    if $\tilde{q}_{\ell,j-1} - \tilde{q}_{\ell,j} \geq |\Delta P^{\min}_{\ell,k+j}| - \epsilon$ ***and*** $\tilde{q}_{\ell,j} \leq P^{\max}_{\ell,k+j}$ **then**
      $r^{\mathrm{down}}_{\ell,j} = 1$
    else if $\tilde{q}_{\ell,j-1} \geq P^{\max}_{\ell,k+j} - \epsilon$ ***and*** $r^{down}_{\ell,j+1} = 1$ **then**
      $r^{\mathrm{down}}_{\ell,j} = 1$
    end
  else
    if $\tilde{q}_{\ell,j-1} - \tilde{q}_{\ell,j} \geq |\Delta P^{\min}_{\ell,k+j}| - \epsilon$ ***and*** $\tilde{q}_{\ell,j} \leq P^{\max}_{\ell,k+j}$ **then**
      $r^{\mathrm{down}}_{\ell,j} = 1$
    end
  end
end

The iterative DMPC procedure is shown in Algorithm 1. This algorithm optimizes the objective function of every agent whereas the balance between generation and demand is achieved. First, optimization parameters and variables are initialized. The last available state of the system can be used for variables initialization. Then, the iterative algorithm is solved for each interval in a closed-loop manner until the operation horizon is reached. Since this is a distributed approach, optimization problems can be solved in parallel, but controllers must be coordinated for information sharing. After participants finish their optimization process, the central operator receives data from them and

Algorithm 4: Ramp-up forward corrective algorithm

```
Inputs: π_k̃, H_p, P_{ℓ,k̃}, P*_{ℓ,k−1}, and r^up_{ℓ,k̃}
Outputs: r^up_{ℓ,k̃}, q^lim_{ℓ,k̃}
for j = 0 to H_p do
    q^lim_{ℓ,j} = P^max_{ℓ,k+j}
    if r^up_{ℓ,j} = 1 then
        if j=0 then
            if P*_{ℓ,k−1} + ΔP^max_{ℓ,k+j} ≤ P^max_{ℓ,k+j} then
                q^lim_{ℓ,j} = P*_{ℓ,k−1} + ΔP^max_{ℓ,k+j}
                if P_{ℓ,k+j+1|k} − q^lim_{ℓ,j} ≥ ΔP^max_{ℓ,k+j} − ϵ then
                    r^up_{ℓ,j+1} = 1
                end
            end
        else
            if r^up_{ℓ,j−1} = 1 then
                if q^lim_{ℓ,j−1} + ΔP^max_{ℓ,k+j} ≤ P^max_{ℓ,k+j} then
                    q^lim_{ℓ,j} = q^lim_{ℓ,j−1} + ΔP^max_{ℓ,k+j}
                    if j < H_p and P_{ℓ,k+j+1|k} − q^lim_{ℓ,j} ≥ ΔP^max_{ℓ,k+j} − ϵ then
                        r^up_{ℓ,j+1} = 1
                    end
                end
            else
                q^ideal = max((π_{j−1} − b_ℓ) / (2a_ℓ), 0)
                if q^ideal + ΔP^max_{ℓ,k+j} ≤ P^max_{ℓ,k+j} then
                    q^lim_{ℓ,j} = q^ideal + ΔP^max_{ℓ,k+j}
                    if j < H_p and P_{ℓ,k+j+1|k} − q^lim_{ℓ,j} ≥ ΔP^max_{ℓ,k+j} − ϵ then
                        r^up_{ℓ,j+1} = 1
                    end
                end
            end
        end
    end
end
```

updates the system demand and the energy price. Finally, every participant applies the first optimal control signal of the sequence and the central operator obtains feedback from the real system.

Conventional generators must apply additional steps for achieving balance if ramps are enforced. In Section 4.3, we have shown that it is necessary to identify when ramps are enforced in order to balance the power system (Proposition 1 and Proposition 2). The Algorithm 2 and Algorithm 3 allow us to find when ramps are enforced by providing flags (1 if active, 0 otherwise), $r^{\text{up}}_{\ell,j}$ stands for an active ramp-up and $r^{\text{down}}_{\ell,j}$ for an active ramp-down. Those algorithms use the hypothetical behavior of generators

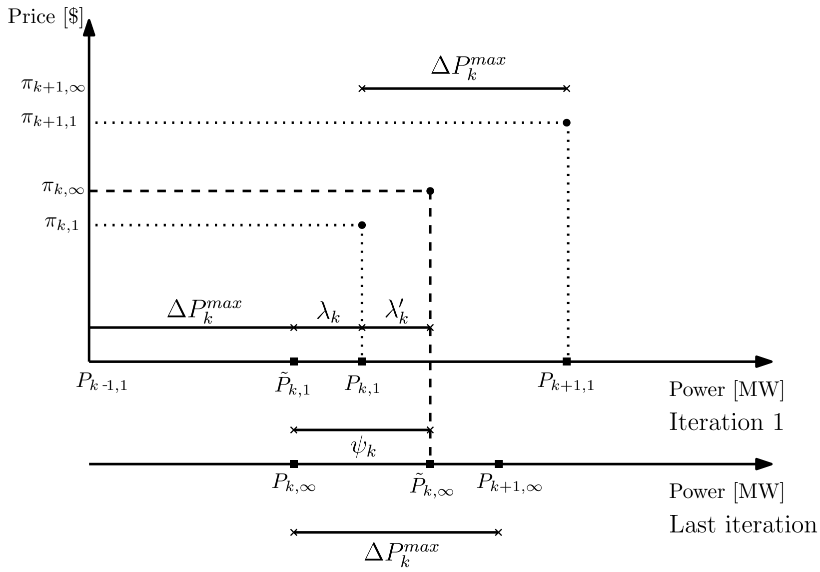


Fig. 4.1 Analysis of corrections for ramp-rate constraints.

without constraints, i.e., their natural response ($\tilde{\boldsymbol{q}}_\ell$) driven by the energy price, and analyze the output change between intervals of that hypothetical generation to verify if it exceeds the allowed limits. Algorithm 4 and Algorithm 5 find the generation limits of each generator in every interval for achieving balance. If ramp flags are not activated in an interval, the generation limit is the technical capacity of the generator. Otherwise, the generation limit is found through ideal generation and ramp rate constraints. The premise used for finding generation limits is the system security, i.e., generation must not exceed load (Definition 3). On the one hand, Algorithm 4 is a forward process that for each interval j analyzes what should be the ideal generation of the previous interval $j-1$, if $r_{\ell,j}^{\text{up}} = 1$, and adds to it the ramp constraint for defining generation limits. Since generation limits are more restrictive than hypothetical values, ramp flags must be updated if necessary. On the other hand, Algorithm 5 is a mixed backward and forward process that finds the ideal generation of the current interval j, if $r_{\ell,j}^{\text{down}} = 1$, and defines generation limits for the previous interval $j-1$ by adding to it the ramp constraint. As in Algorithm 4, the ramp-down back-forward corrective algorithm updates ramp flags if necessary. Fig. 4.1 shows the analysis behind Algorithm 4 (the same kind of analysis applies to Algorithm 5). For this example we evaluate two time instants ($H_p = 1$) at k, and both the initial and final iterations. Prices $\pi_{k,1}$ and $\pi_{k+1,1}$ are the electricity values for iteration 1, while $P_{k,1}$ and $P_{k+1,1}$ are the optimal generation of plant 1. Consider that the ramp-rate is enforced for both instans k and $k+1$ and that this solution is not secure as the desired output should be $\tilde{P}_k, 1$. Thereby, it is necessary to decrease the output $P_{k,1}$ such that a different generator provides the lack of energy λ_k. For providing a signal to another generator and fulfill the load requirement, the microgrid operator should increase the price to $\pi_{k,\infty}$. However, when the price increases, the plant 1 wants to generate $\tilde{P}_{k,\infty}$. In order to avoid that undesired behavior, Algorithm 4 finds the auxiliar variable ψ_k and includes it in the objective function. As a result, at the final iteration the optimal configuration for plant 1 is $P_{k,\infty}$ and $P_{k+1,\infty}$. The desired power $\tilde{P}_{k,1}$ is determined through algorithm 4 by finding q^{ideal} or by adding the ramp-rate limit to the initial condition $P_{k-1,1}$ if the ramp is enforced at $k = 1$. We have separately presented Algorithms 2-5 for a better understanding, but they can be integrated when implemented in order to decrease the computational time.

When all participants of the network have finished their optimization problems and conventional generators have completed their additional algorithms, the central operator must update the load for conventional generators, the load for renewable, and the energy price through Algorithm 6. In that algorithm, the central operator analyzes ramp flags and finds the new energy price by taking into account the current generation limits. In Algorithm 6 the *price* function is a method that uses the microgrid operator for finding the electricity price with inputs of load and capacity of generators, e.g., market clearing.

One iteration of the proposed DMPC is depicted in Fig. 4.2. Every group of participants is delimited with a color block. Each participant in the group solves an optimization problem and shares information with its neighbors. A consensus algorithm is applied in information blocks to share data with participants of the group or to find information for the microgrid operator. Remaining blocks represent an step related to an algorithm or an equation. The block of conventional generators is the more complex because of the additional algorithms for achieving balance under active ramp rate constraints.

4.5 Case Study and Results

4.5.1 Case Study

In order to demonstrate the performance of the proposed algorithm, we use the NYISO load pattern along with some elements to form a microgrid. The example consists of three conventional generators, a wind generator without ESS, two solar panels (one with ESS and the other one without), and a stand-alone ESS. The magnitude of NYISO load pattern is scaled down for simulating a microgrid demand in 1-hour and 5-minute

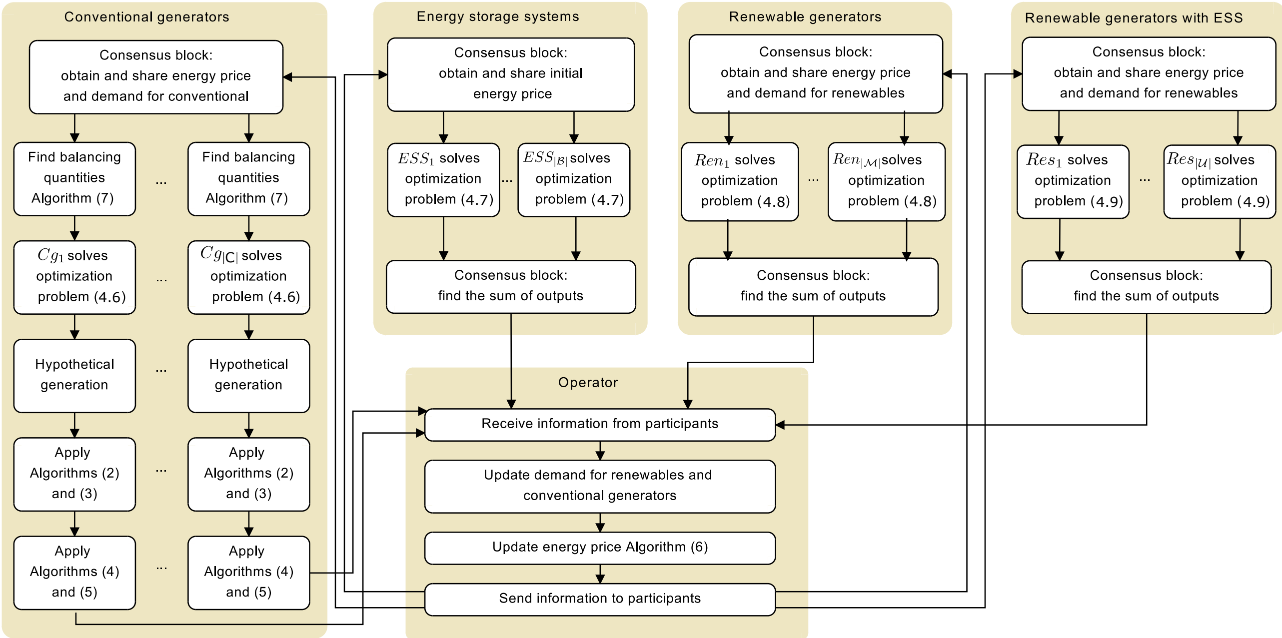


Fig. 4.2 Flow diagram of a DMPC iteration.

periods. Specifications of the generators and ESS in the microgrid are shown in Tables 4.1 and 4.2, respectively. Marginal costs in this case are very similar to those used in Chapter 3 and renewable-based power plants have been modeled with marginal costs very close to zero. This simulation case shows how the proposed approach achieves a balance between generation and load while complying with ramp-rate constraints of generators.

4.5.2 Results and discussion

The economic dispatch results are shown in Figs. 4.3-4.6. Fig. 4.3 shows how the algorithm achieves balance when load can be fulfilled with renewable resources. Negative values in dispatch represent the charging status of the stand-alone battery, and they appear prior to a demand increase, i.e., $k = 4, 5$ and $k = 15, 16$. Then, the ESS delivers energy to the system when demand is high, i.e., $k = 9, 11, 12$ and $k = 19, 20$. This behavior is the result of a price-responsive battery that wants to charge when price is low and discharge when price is high, that is when demand is low and high, respectively.

Importance of the forecast period is depicted in Fig. 4.4, where two different forecast periods ($H_p = 0$ and $H_p = 10$) are used for the proposed distributed economic dispatch problem. One of the most important features of the proposed algorithm is the fact that

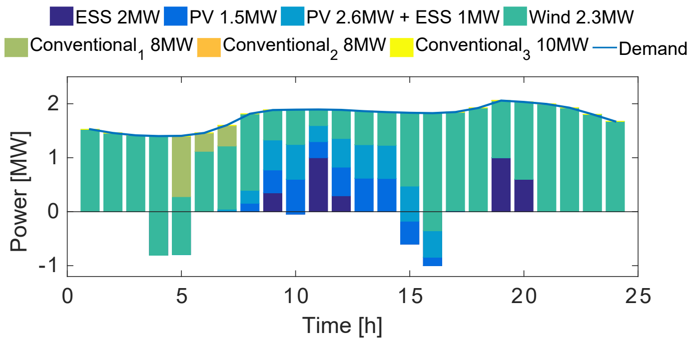


Fig. 4.3 Energy balance of DMPC by using available renewable generation.

it achieves balance without using an explicit coupled constraint in the optimization problem. Instead, balance arises through the price given by the operator, the algorithms used by conventional power plants, and formulation of renewable generators. Moreover, balance under ramp-rate constraints depends on technical features of generators and length of forecast period. Fig. 4.4(a) presents the results of economic dispatch when forecast period is 0, where there is imbalance as total generation exceeds load. This behavior compromises the power system security. On the other hand, Fig. 4.4(b) shows generation schedule when forecast period is 10. Since information of the next 10 hours is available in the present, generators are aware of price changes and adjust their output for achieving balance in every hour. For instance, even though conventional$_2$ could produce more energy at $k = 5$, it does not because its ramp would be enforced and the system would present an imbalance at $k = 6$. In addition, if there is no enough information of future prices, energy storage systems would not have incentives to draw electricity from the network and arbitrage the market.

Fig. 4.5 presents two solutions that do not comply with thesecurity of microgrid operations as the total generation exceeds load in certain hours. The forecast period is a very important parameter of the MPC since it guarantees feasible and optimal solutions in the presence of ramp-rate constraints. Fig. 4.5(a) shows the importance of calibrating this parameter although results might be good at a first sight. Case in point, the DMPC with a forecast period of 2 hours (Fig. 4.5(a)) achieves the balance in almost every hour but it presents a small generation excess at $k = 25, 26, 27$. In contrast, the DMPC with a prediction horizon of 10 hours (Fig. 4.4(b)) achieves the balance in every hour. Nevertheless, having a large forecast period increases the computational burden as decision variables increase in the DMPC. Here, the microgrid participants can choose between a very accurate DMPC with a large forecast period or an efficient DMPC with a small forecast period and leave the exact balance task

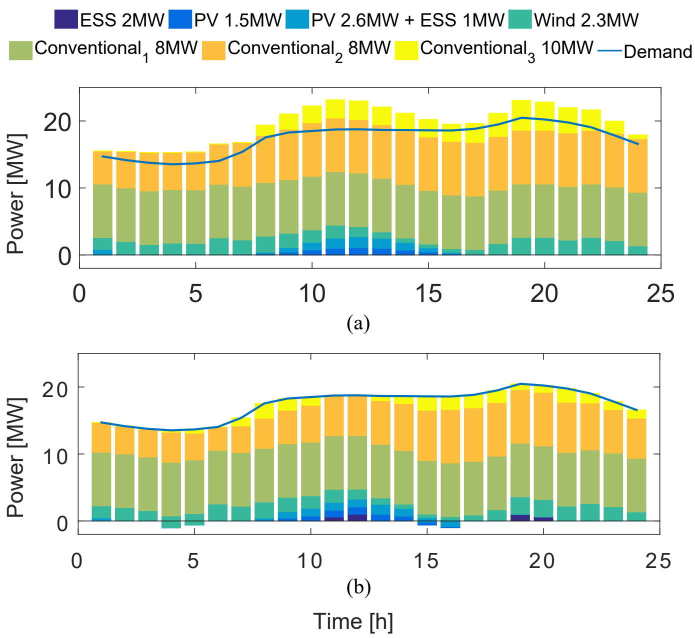


Fig. 4.4 Dispatch for one day applying the DMPC and different forecast periods. (a) DMPC with $H_p = 0$. (b) DMPC with $H_p = 10$.

to primary local controllers. The decision will be related to the dispatch periodicity and computation time of the algorithm. That is, if dispatch is to be solved every 5 minutes, the DMPC computation time must be less than that time. Even though the forecast period parameter is very important in this optimization problem, it is not sufficient to obtain implementable solutions. Fig. 4.5(b) shows the dispatch behavior when the forecast period is 10, but the proposed algorithms for conventional generators are not applied. Total generation exceeds load at every hour, thereby the power system security is compromised. The proposed algorithms for conventional generators allow the microgrid to be balanced even when ramps are enforced. If such algorithms are not used, the proposed distributed economic dispatch without an explicit coupled balance constraint is not implementable.

We have shown so far that the proposed DMPC provides an efficient and implementable solution for the ultra-short-term economic dispatch problem in a microgrid. However, better solutions can be achieved if an algorithm that emulates a centralized dispatch is used instead, such as the DDMPC proposed in [66]. The main drawback of the DDMPC is its unexpectedly long computational time, which is higher than the DMPC approach because of the large number of decision variables, the coupling constraints, and the dual-decomposition algorithm which requires more interations to converge. In a hourly dispatch the iterations amount of the DDMPC is not an

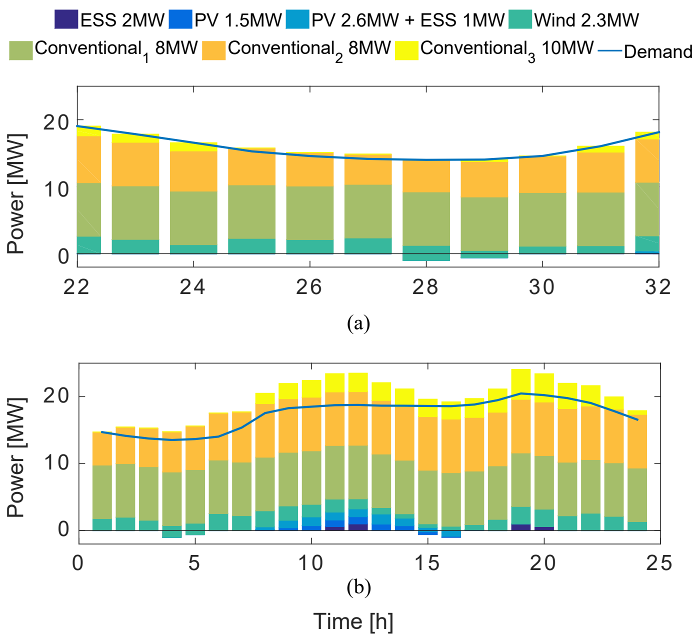


Fig. 4.5 Undesirable dispatch for one day applying the DMPC. (a) DMPC with $H_p = 2$. (b) DMPC without proposed algorithms and $H_p = 10$.

issue, but it might become a restraining factor for the intra-hour dispatch (e.g., every 5 minutes). Fig. 4.6 presents a comparison between DMPC and DDMPC for the hourly economic dispatch. The main difference of the two approaches is that conventional$_1$ in the DDMPC (Fig. 4.6(b)) decreases its output at hours $k = 2, 3, 6, 7, 11$, and 12 when conventional$_2$ increases its output to minimize the use of the most expensive generator (conventional$_3$). On the other hand, conventional$_1$ in the proposed DMPC produces power at its maximum limit (8 MW) in every hour since it wants to maximize its individual profit. Accordingly, conventional$_2$ limits its generation to comply with its ramping constraints and conventional$_3$ is dispacthed for more hours, thereby increasing the operation cost. In terms of the ultra-short term economic dispatch, Table 4.5 shows the results of DDMPC and DMPC applied to the case study every 5 minutes for 1 hour and 24 hours. The DDMPC presents better results regarding the operational cost, but the proposed DMPC reaches very good results with less iterations (approximately 6% of the DDMPC iterations). Operational costs of DMPC presents an excess close to 2% with respect to the operational cost of DDMPC.

Moreover, we have tested the computational complexity and scalability of DMPC compared with a centralized MPC and the DDMPC. These results are depicted in Tables 4.3 and 4.4. Table 4.3 shows the simulation time in function of amount of generators per each economic dispatch method and for one time step with $H_p = 13$.

The DMPC converges very fast and has the lowest computational time among all configurations. Regarding the other methods, performance of the centralized MPC is very fast, but it grows exponentially as generators increase, reaching almost two hours when 1000 power plants are considered. On the other hand, DDMPC computational time is not as fast as DMPC or the centralized approach for small scale systems, but is much faster than centralized MPC as generators increase. Both computational times of DDMPC and DMPC approaches do not vary so much when a new power plant is added to the system. This result was expected as we mentioned before that one advantage of using distributed approaches is their scalability because of parallelization. Table 4.4 shows the simulation time in function of prediction horizon per each economic dispatch method and for one time step with 20 generators. The proposed DMPC has the lowest simulation time for every prediction horizon evaluated. Centralized MPC starts very fast, but its computational time increases exponentially when prediction horizon is large. Indeed, we did not calculate its behavior for $Hp = 800 - 2000$ because of memory capacity. On the other hand, DDMPC computational time increases as prediction horizon is larger, and it is higher than the simulation time of DMPC. From these results, we can identify that DMPC is the fastest method and is feasible for ultra-short term applications. However, from the data shown in Fig. 4.6 and Table 4.5, its economic performance is less efficient than the optimal solution of the DDMPC. Because of this trade-off, an alternative is to combine both approaches for very short-term applications. For instance, some of the principles stated in [52] can be applied. Notice that this computational analysis evaluates independently the impact of generators amount and prediction horizon. Nevertheless, if growth of both variables is considered at the same time, the need of using DMPC becomes more critical. In summary, DDMPC presents better results in economic terms, but the DMPC obtains efficient results with very few iterations. However, the economic impact is more evident in the hourly economic dispatch where it is better to use the DDMPC.

The proposed DMPC is applicable to the ultra-short-term dispatch, but its solution is less efficient if compared with the optimal solution of the DDMPC. Since DDMPC is heavier in computational terms, its implementation for very short-term applications might not be feasible. An alternative to address that issue is to combine both approaches for very short-term applications. For instance, some of the principles stated in [52] can be applied. Synchronization of such algorithms is not an easy task. Indeed, we think that it is a very interesting research topic where the ultra-short term economic dispatch can achieve more efficient solutions.

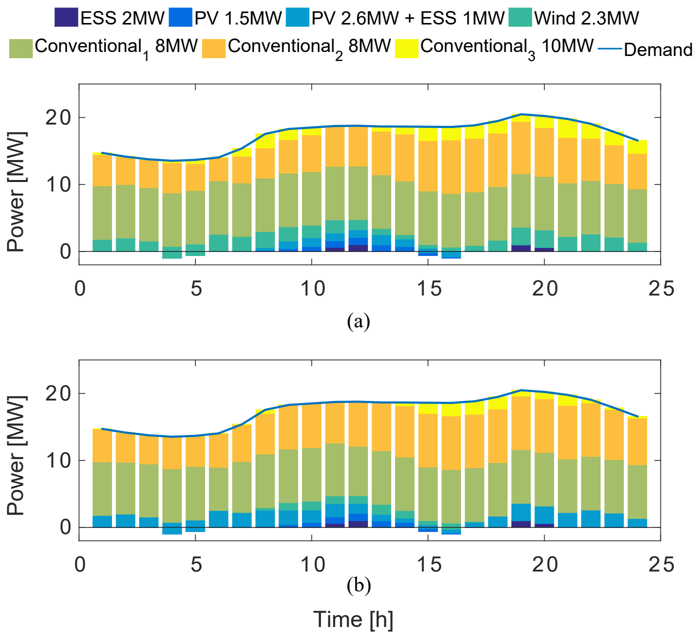


Fig. 4.6 Dispatch for one day applying DDMPC and DMPC approaches. (a) DMPC with $H_p = 10$. (b) DDMPC with $H_p = 10$.

4.6 Concluding Remarks

This chapter proposes a distributed MPC for solving the ultra-short term economic dispatch, which achieves balance between energy and load through price signals from the operator by taking into account ramp-rate constraints. Balance of energy can be achieved by renewable generators in the case that their current availability is larger than load, and by conventional generators which use novel algorithms that identify enforced ramps and comply with the system security. Balance of energy is fulfilled even though generators pursue their own benefit maximization. In addition, private information (e.g., benefits or costs) is not shared with other agents.

Since DDMPC might not be feasible for the ultra-short term dispatch because of decision variables amount, computational requirements, and number of iterations, and intra-hour dispatch is being more relevant for current smart grids, the speed and efficiency of DMPC become critical contributions of this chapter. Formulation of conventional generators in the proposed approach is equivalent to the DDMPC optimization problem, but Lagrange multipliers are found algorithmically instead of including them as decision variables. This feature decreases computational burden, whereas generators find an optimal output according to their own benefit. Furthermore, formulation of elements commonly used in microgrids has been included. First, renewable power plants have been considered and defined as generator-only and generator with energy storage system, which are able to balance the microgrid. Second, stand-alone energy storage systems have been defined with arbitrage capabilities for maximizing net profit.

The DMPC performance has been successfully tested for different situations. First, a case where load is lower than renewable availability was simulated for verifying that balance is attained with the proposed formulation for renewable generators. Second, impact of the MPC forecast period was analyzed as a larger H_p implies higher computational time but ensures balance. Third, behavior of not using the proposed algorithms was assessed with a large forecast period. Energy balance was not achieved in that case, thus showing that a large forecast period is not enough for balancing a power system with ramp-rate constraints. Finally, solutions of the hourly economic dispatch for both the DDMPC and the proposed approach were obtained. Here, it was verified that the DDMPC approach leads to better results in economic terms since the algorithm finds a solution that minimizes operational costs in a distributed manner. However, the DDMPC might not be feasible for the ultra-short term dispatch or would require high computational resources. These results were verified by simulating the ultra-short term economic dispatch (every 5 minutes) and analyzing the operational cost along with the iterations required to solve the problem. The DMPC finds efficient solutions with fewer iterations, so that it might be better for the ultra-short term economic dispatch. However, a better solution would be the integration of both algorithms so that in the ultra-short term the system operation is closer to the optimal.

In the next chapter the authors propose to integrate DDMPC with DMPC under a common stochastic optimization based framework due to the fact that microgrid operations are facing an increasing number of uncertainties (e.g., volatile renewables, price-reponsive loads). Our main goal is to provide a unified distributed-stochastic MPC approach to solve the microgrid economic dispatch problem effciently, especially for the ultra-short-term one. In addition, the coordination of DDMPC and DMPC approaches is an interesting topic for guiding the implementation of better microgrid operations.

Algorithm 5: Ramp-down back-forward corrective algorithm

Inputs: $\boldsymbol{\pi}_{\tilde{k}}, H_p, \boldsymbol{P}_{\ell,\tilde{k}}, P^*_{\ell,k-1}$, and $\boldsymbol{r}^{\text{down}}_{\ell,\tilde{k}}$

Outputs: $\boldsymbol{r}^{\text{down}}_{\ell,\tilde{k}}, \boldsymbol{q}^{\text{dlim}}_{\ell,\tilde{k}}$

- Backward step:

```
j = H_p
while j ≥ 1 do
    q^dlim_{ℓ,j−1} = P^max_{ℓ,k+j};
    if r^down_{ℓ,j} = 1 then
        if j < H_p then
            if r^down_{ℓ,j+1} = 1 then
                if q^dlim_{ℓ,j} + |ΔP^min_{ℓ,k+j}| ≤ P^max_{ℓ,k+j} then
                    q^dlim_{ℓ,j−1} = q^dlim_{ℓ,j} + |ΔP^min_{ℓ,k+j}|
                    if j > 1 and P_{ℓ,k+j−2|k} − q^dlim_{ℓ,j−1} ≥ |ΔP^min_{ℓ,k+j}| − ϵ then
                        r^down_{ℓ,j−1} = 1
                    end
                end
            else
                q^ideal = max((π_j − b)/(2a_ℓ), 0)
                if q^ideal + |ΔP^min_{ℓ,k+j}| ≤ P^max_{ℓ,k+j} then
                    q^dlim_{ℓ,j−1} = q^ideal + |ΔP^min_{ℓ,k+j}|
                    if j > 1 and P_{ℓ,k+j−2|k} − q^dlim_{ℓ,j−1} ≥ |ΔP^min_{ℓ,k+j}| − ϵ then
                        r^down_{ℓ,j−1} = 1
                    end
                end
            end
        else
            q^ideal = max((π_j − b_ℓ)/(2a_ℓ), 0)
            if q^ideal + |ΔP^min_{ℓ,k+j}| ≤ P^max_{ℓ,k+j} then
                q^dlim_{ℓ,j−1} = q^ideal + |ΔP^min_{ℓ,k+j}|
                if P_{ℓ,k+j−2|k} − q^dlim_{ℓ,j−1} ≥ |ΔP^min_{ℓ,k+j}| − ϵ then
                    r^down_{ℓ,j−1} = 1
                end
            end
        end
    end
end
```

- Forward step:

```
if P*_{ℓ,k−1} − q^dlim_{ℓ,0} ≥ |ΔP^min_{ℓ,k+j}| − ϵ then
    if P*_{ℓ,k−1} − |ΔP^min_{ℓ,k+j}| ≥ q^dlim_{ℓ,0} then
        q^dlim_{ℓ,0} = P*_{ℓ,k−1} − |ΔP^min_{ℓ,k+j}|
    end
    for j = 1 to H_p − 1 do
        if q^dlim_{ℓ,j−1} − |ΔP^min_{ℓ,k+j}| ≥ q^dlim_{ℓ,j} then
            q^dlim_{ℓ,j} = q^dlim_{ℓ,j−1} − |ΔP^min_{ℓ,k+j}|
        end
    end
end
```

Algorithm 6: Price update

Inputs: $H_p, \hat{\boldsymbol{D}}_{\tilde{k}+1}, \boldsymbol{q}^{\text{lim}}_{\ell,\tilde{k}}$, and $\boldsymbol{q}^{\text{dlim}}_{\ell,\tilde{k}}$ for all $\ell \in \mathcal{C}$.
Outputs: $\boldsymbol{\pi}_{\tilde{k}+1}$.
for $j = 0$ *to* H_p **do**
  if $j < H_p$ **then**
    $\pi_{j,\tilde{k}+1} = price(\hat{D}_{j,\tilde{k}+1}, \min(q^{\text{dlim}}_{\ell,j}, q^{\text{lim}}_{\ell,j})$ for all $\ell \in \mathcal{C})$
  else
    $\pi_{j,\tilde{k}+1} = price(\hat{D}_{j,\tilde{k}+1}, q^{\text{lim}}_{\ell,j}$ for all $\ell \in \mathcal{C})$
  end
end

Algorithm 7: Balancing quantities

Inputs: $\boldsymbol{\pi}_{\tilde{k}}, H_p, \boldsymbol{r}^{\text{down}}_{\ell,\tilde{k}}, \boldsymbol{r}^{\text{up}}_{\ell,\tilde{k}}, \boldsymbol{q}^{\text{lim}}_{\ell,\tilde{k}}$, and $\boldsymbol{q}^{\text{dlim}}_{\ell,\tilde{k}}$.
Outputs: $\boldsymbol{\Psi}_{\ell,\tilde{k}}$.
for $j = 0$ *to* $H_p - 1$ **do**
  if $r^{down}_{\ell,j+1}$ ***or*** $r^{up}_{\ell,j}$ **then**
    $\Psi_{\ell,k+j} = 2a_\ell \left[\max\left(\frac{\pi_j - b_\ell}{2a_\ell} - \min(q^{\text{dlim}}_{\ell,j}, q^{\text{lim}}_{\ell,j}), 0\right)\right]$
  else
    $\Psi_{\ell,k+j} = 0;$
  end
  if $j = H_p$ ***and*** $r^{up}_{\ell,j} = 1$ **then**
    $\Psi_{\ell,k+j} = 2a_\ell \left[\max\left(\frac{\pi_j - b_\ell}{2a_\ell} - q^{\text{lim}}_{\ell,j}, 0\right)\right]$
  else
    $\Psi_{\ell,k+j} = 0;$
  end
end

Table 4.1 Parameters of generators in the microgrid

Generator	a $[\frac{\$}{\text{MW}^2}]$	b $[\frac{\$}{\text{MW}}]$	$P^{\min}$ [MW]	$P^{\max}$ [MW]	$\Delta P^{\min}$ $[\frac{\text{MW}}{5\text{min}}]$	$\Delta P^{\max}$ $[\frac{\text{MW}}{5\text{min}}]$
Conventional$_1$	0.5	1	0	8	-2	2
Conventional$_2$	1	10	0	8	-0.06	0.06
Conventional$_3$	7	35	0	10	-4	4
Wind	0	0.2	0	2.6	-2.6	2.6
PV	0	0.15	0	1.5	-1.5	1.5
PV+ESS	0	0.1	0	2.3	-2.3	2.3

Table 4.2 Parameters of ESS in the microgrid

Battery	b_ℓ $[\frac{\$}{\text{MW}}]$	$P^{\min}$ $[\frac{\$}{\text{MW}}]$	$P^{\max}$ [MW]	$\text{SOC}^{\min}$ [MW]	$\text{SOC}^{\max}$ $[\frac{\text{MW}}{5\text{min}}]$	P^{cap} $[\frac{\text{MW}}{5\text{min}}]$
ESS	0.1	-0.167	0.167	0	1	1
ESS(PV)	0.05	-0.84	0.084	0	1	2

Table 4.3 Simulation time in function of amount of generators per each economic dispatch method and for one time step with $H_p = 13$

# of Generators	Centralized MPC[s]	DDMPC[s]	DMPC[s]
3	0.118	4.400	0.0788
10	0.207	4.540	0.0804
100	2.684	4.549	0.0804
200	7.208	4.630	0.0812
300	13.18	6.150	0.0928
400	21.69	6.780	0.2924
500	31.20	7.280	0.3204
750	54.88	7.212	0.3103
900	1988	6.854	0.3201
1000	6944	7.327	0.3214

Table 4.4 Simulation time in function of prediction horizon per each economic dispatch method and for one time step with 20 generators

H_p	Centralized MPC[s]	DDMPC[s]	DMPC[s]
13	0.39	5.48	0.13
24	0.75	6.41	0.19
36	1.18	7.50	0.25
72	3.56	10.56	0.43
200	14.29	29.40	1.1
300	27.12	45.47	1.61
400	44.51	65.91	2.22
500	67.64	85.81	2.83
600	1574.00	106.50	3.43
700	3843.98	131.48	4.13
800	No register	162.60	4.78
1000	No register	212.46	6.14
1200	No register	267.10	7.55
1500	No register	370.87	9.9
2000	No register	576.31	15

Table 4.5 Comparison of DDMPC and DMPC for the ultra-short term

	DDMPC		DMPC	
	1 hour	24 hours	1 hour	24 hours
Operational cost	1352.1	49091.3	1353.5	49943.1
Total iterations	2629	32905	108	2270
Average iterations	202.2	113.8	8.3	7.8

Chapter 5

Distributed Stochastic Economic Dispatch via Model Predictive Control and Data-Driven Scenario Generation

Renewable energy sources, active demand participation, and prices fluctuation have introduced variability and stochasticity in power systems operation. Accordingly, operators are looking for utilizing available forecast information in order to enhance the system response to unpredictable changes. This chapter considers a data-driven scenario generation method within two distributed techniques that solve the economic dispatch problem while reducing uncertainty impacts on operation costs. At first, the hourly and ultra-short term dispatches are presented as stochastic programming problems by relying on model predictive control, which also address the concern of variability and uncertainty. Second, since ultra-short term dispatch does not optimize the social benefit, we provide a master-slave configuration that allows operators to efficiently coordinate it with the hourly approach and obtain better operation costs. The simulation results validate the advantages of using stochastic programming instead of deterministic approaches under smart grids framework.

5.1 Introduction

In the last years, power systems have experienced several changes as a result of smart grids penetration into distribution systems. Smart grids have several elements, such as demand response, storage systems, and renewable resources, that come with challenges for their large scale deployment. Since the cost of renewable resources has decreased, especially for solar photovoltaics [33], and there is a worldwide interest in reducing greenhouse gas emissions [62], the installation of renewable-based power plants has gathered more attention.

One of the most difficult challenges to address by the system operator is the uncertainty related to these elements, and how it affects both the planning and operation of the electricity network. For instance, a common problem of solar photovoltaic power is the duck curve shown by the California independent system operator [21]. This curve shows the high imbalance of solar power generation and the peak load of the system, and represents a problem for covering the increased required ramp. Another example is the issue associated to unexpected decreases of renewable resources (e.g., wind speed) and the need to turn on an expensive power plant for supplying the system load. On the other hand, if availability of renewables increases and load drops, total generation may surpass the system demand thereby compromising the system security. This chapter is motivated by the uncertainty challenge and its impact in the power system operation, i.e., the economic dispatch.

The economic dispatch is an optimization problem that looks for minimizing operation costs or maximizing global benefits of the system as it is usually solved by a centralized agent. Here, the system load must be supplied by a set of generators that have different technical and economic characteristics. Several techniques have been used for solving this optimization problem [69]. These approaches are usually applied by a centralized controller that finds optimal outputs for every generator in the system. However, centralized methods may experience *curse of dimensionality* [8] issues as stochastic variables are considered in the optimization problem. In addition, dimensionality is critical when solving a dynamic dispatch instead of a static one. In order to tackle the curse of dimensionality when handling stochastic variables in a dynamic environment, we propose to use distributed approaches ([66, 67]) based on model predictive control.

MPC techniques include deterministic and stochastic approaches for centralized and distributed control strategies. Several authors have worked on MPC methods applied to the economic dispatch problem by considering deterministic and stochastic approaches for centralized and distributed control strategies. In [54], Patrinos et al. proposed a stochastic market-based dispatch problem, considering conventional generators, renewables, and energy storage. They used scenarios generation in order to include uncertainty of load, prices, and generation. A two-stage stochastic energy management system was proposed by Olivares et al. in [52]. In the first stage the authors solve a stochastic UC, and in the second stage they solve a shrinked horizon optimal power flow to deal with network constraints. Kou et al. in [39] used MPC to manage batteries in systems with wind power. The authors claim that the main advantage is the use of non-Gaussian wind power uncertainties along with chance constraints. In [80], Zhu et al. provided a stochastic MPC that uses decomposition algorithms (scenario and temporal) together with an iterative update for scenarios convergence. A hierarchical multi-period dispatch that uses a master MPC and slave MPCs for subgrids was proposed by Fortenbacher et al. in [26]. The authors used an optimal power flow to deal with network contraints. Alqurashi et al. in [4] provided a multi-stage MPC to compensate forecast error in a scenario-based stochastis dynamic dispatch. Del Real et al. in [2] designed a distributed MPC based on Lagrange-MPC. The proposed optimization problem minimized both economic and environmental costs in interconnected energy hubs. Ilić et al. in [31] proposed a method known as DYMONDS, which has both centralized and distributed features. They showed that a fully distributed algorithm may not reach a balance between generation and demand. The authors applied MPC to solve economic and environmental dispatch problems with intermittent generation resources [72]. In [25], Ersdal et al. designed a stochastic nonlinear MPC for automatic generator control, and compared it with a multi-stage nonlinear controller. The authors used scenario trees for including uncertainty. A distributed MPC to operate a microgrid was proposed by Zheng et al. in [76]. The authors defined an MPC controller for every element in the microgrid. However, they do not include ramp-rate limits.

To the best of our knowledge, there is a lack of research on distributed MPC-based methods that consider stochasticity in the economic dispatch problem. The management of distributed methods with uncertainty may change with respect to deterministic approaches, specially when dealing with coupled constraints. The task of combining distributed methods with stochastic approaches is more complex when there is a coupled constraint such as energy balance. In this chapter, we provide two MPC-based distributed methods that consider uncertainty, which is addressed through the data-driven scenario generation approach. The MPC-based methods solve the hourly and ultra-short term dispatch, respectively. In addition, we combine both methods in a master-slave configuration with termination constraints in order to enhance the electric system operation. The main contribution of this research is the stochastic approach of two economic dispatch problems that achieve balance of power and demand in a distributed manner, and the combined operation of them in a smart grid environment.

The remainder of this chapter is organized as follows. In Section 5.2 the background of economic dispatch and model predictive control is provided. Section 5.3 describes the stochastic programming approach. Details of the data-driven approach and stochastic formulation for different participants are provided. In Section 5.4 coordinated operation of hourly and ultra-short term approaches is explained in detail. The case study and results are presented in Section 5.5. Finally, in Section 5.6 conclusions are drawn.

5.2 Background for the Economic Dispatch

5.2.1 Economic dispatch

To describe the economic dispatch problem consider m generators from the set $\mathcal{N} = \{1, \ldots, m\}$, with limits stated as $P_v^{\min}$ and $P_v^{\max}$, ramp restrictions of $\Delta P_v^{\min}$ and $\Delta P_v^{\max}$, and a generation cost function given as $C_v(P_{v,k}) = a_v P_{v,k}^2 + b_v P_{v,k}$, where $v = 1, \ldots, m$. Given the set of generators $\mathcal{N}$, in a centralized approach the system operator determines the scheduling of generators that can meet the time-variant load Q at every time step. The centralized economic dispatch can be defined as a static or dynamic optimization problem where power system operators minimize system operation costs by considering several constraints on load, supply, generators capacity, and ramping-rates [12] as follows:

$$\underset{P_{v,k}}{\text{minimize}} \quad \sum_{v=1}^{m} C_v(P_{v,k}) \tag{5.1a}$$

subject to

$$\sum_{v=1}^{m} P_{v,k} = Q_k, \tag{5.1b}$$

$$P_v^{\min} \leq P_{v,k} \leq P_v^{\max}, \tag{5.1c}$$

$$\Delta P_v^{\min} \leq \Delta P_{v,k} \leq \Delta P_v^{\max}. \tag{5.1d}$$

In different researches, we proposed a distributed dual-decomposition model predictive control to solve the centralized economic dispatch problem in a distributed manner [66]. Although the DDMPC is feasible for the hourly economic dispatch, it might not be sufficient to deal with the intra-hour economic dispatch because of its computational burden. For solving such optimization problem in a faster distributed approach, we use the MPC method (Section 2.2.2) and the average consensus algorithm (Section 2.2.2 and Section 4.2.1).

5.3 Stochastic Programming

The uncertainty associated to renewable resources, load, and energy price, affects the performance and operation of power systems since deterministic approaches are mainly used. Deterministic solutions lose efficiency as the penetration of randomness increases. The importance of considering uncertainty in optimization problems was mainly discused by Dantzig [20] who proposed linear optimization approaches under uncertainty. In the last years, several authors have proposed different methodologies for including random variables in both the objective function and constraints of an optimization problem ([10, 7, 34, 17]). Sahinidis et al. [58], Birge [13], Infanger [32], and Chen et al. [18] described and analyzed different methods that include uncertainty in optimization problems. From the analysis, we have identified that chance constraints, robust optimization, and stochastic programming are the more extended alternatives. In addition, Zheng et al. [74] have discussed stochastic methods for applications in power systems. According to the nature of distributed optimization formulations stated in [66] and [67], chance constraints and robust optimization are not applicable since those optimization problems are always feasible. Thereby, stochastic programming is the method used in this research for addressing the distributed economic dispatch problem.

One of the key features of stochastic programming is the definition of scenarios, which are associated to representative values of uncertain variables. There are different methods for generating several scenarios instead of making assumptions about the behavior of the uncertain variable ([22, 23, 27]). From the literature review analysis we chose to use a data-driven approach that not only relies on the moment matching problem but combines it with a distribution-matching feature.

5.3.1 Data-driven scenario generation

This section explains the method proposed by Calfa et al. [15], where the authors explored different alternatives for generating scenarios in a multi-stage environment. First, the moment matching method, originally proposed by Høyland et al., is described by the following optimization problem.

$$\begin{aligned} \underset{x,p}{\text{minimize}} \sum_{i \in \mathcal{D}} w_i \left(f_i(x,p) - \chi_i \right)^2 \\ s.t. \sum_{j=1}^{N} p_j = 1 \end{aligned} \tag{5.2}$$

In this case, the objective is to minimize the deviation of an statistical property i of the sets $\mathcal{X}$ and $\mathcal{P}$ from that obtained with the historical data. This is a distribution-free approach since it does not require specific parameters for modeling uncertainty. Conversely, target statistics are obtained directly from the data sample. The most used statistics in this method are the mean and central moments, i.e., variance, skewness, and kurtosis. The optimization problem (5.2), known as L^2 MMP, is non-convex and non-linear, and its complexity increases as higher moments are included in the objective function. Other alternatives for solving the MMP are to minimize the L^1-norm (absolute value) or the L^∞-norm (highest value) of the deviation.

Although the MMP provides distributions that match statistical properties of historical data, it is not guaranteed that such distributions exhibit a similar shape. That is, the cumulative distribution function and probability density functions are not similar. This is an undesired contidition because the result of solving (5.2) can be a degenerate solution that do not represent real data uncertainty. In order to enhance the MMP approach, Calfa et al. [15] proposed a distribution matching problem that, additionally to matching statistical properties, looks for matching the cumulative distribution function of the data. The DMP uses an approximation to the empirical cumulative distribution function that is an estimator of the true CDF. The CDF represents the probability that a random variable x takes a value less or equal than $\tilde{x}$. The ECDF proposed by van der Vaart [65] is defined as

$$ECDF(\tilde{x}) = \frac{1}{N} \sum_{j=1}^{N} g(x_j, \tilde{x}) \tag{5.3}$$

where

$$g(x_j, \tilde{x}) = \begin{cases} 1 & x_j \leq \tilde{x} \\ 0 & \text{otherwise} \end{cases} \tag{5.4}$$

In addition, Calfa et al. [15] proposed to use the generalized logistic function (GLF) in order to smoothly include the ECDF in the optimization problem. The GLF

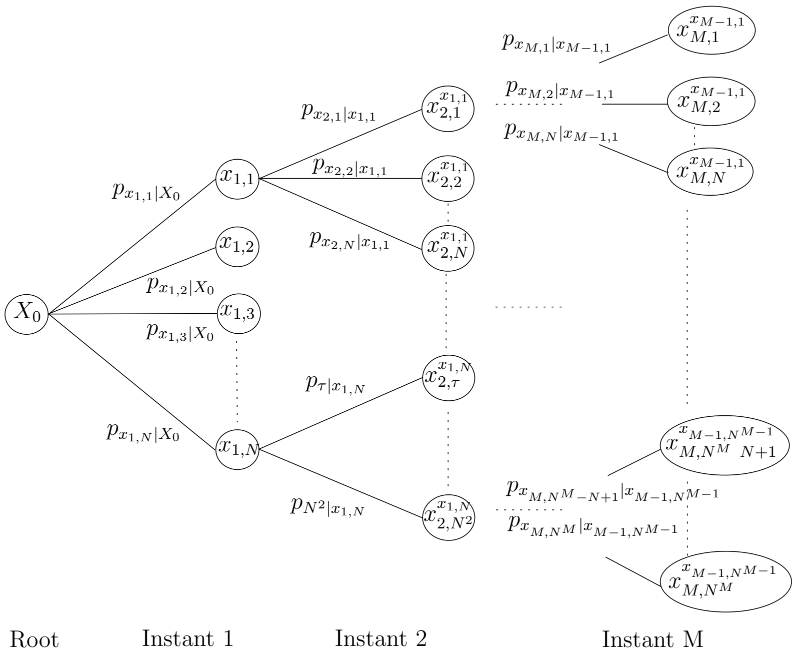


Fig. 5.1 Scenario tree for a multi-stage approach.

approximation is valid as most CDFs are sigmoidal. This function is defined as

$$GLF(\tilde{x}) = \beta_0 + \frac{\beta_1 - \beta_0}{(1 + \beta_2 e^{-\beta_3 \tilde{x}})^{\frac{1}{\beta_4}}} \tag{5.5}$$

After estimating the parameters β of the GLF, the ECDF is smoothly included in the optimization problem (5.2) as follows:

$$\begin{aligned} &\min_{x,p} \sum_{i \in \mathcal{D}} w_i \left(f_i(x,p) - \chi_i\right)^2 + \sum_{j=1}^{N} \left(EC\hat{D}F(x_j) - \sum_{\tilde{j}=1}^{j} p_{\tilde{j}} \right)^2 \\ &s.t. \sum_{j=1}^{N} p_j = 1 \\ &\quad\; x_j \le x_{j+1}, \quad \forall j = 1, \ldots, N-1 \end{aligned} \tag{5.6}$$

where $EC\hat{D}F$ is the empirical cumulative distribution function approximated with a GLF. In order to apply this optimization problem, it is necessary that nodes in the tree are ordered. This condition is ensured with the last constraint in problem (5.6).

5.3.2 Distributed stochastic formulation

In order to include uncertainty in the economic dispatch problem by using stochastic programming, we modify the formulation for the hourly economic dispatch (proposed in [66]) and the ultra-short term economic dispatch (proposed in [67]) as follows.

• Hourly economic dispatch: the following distributed stochastic optimization problem is based on the distributed deterministic formulation proposed in [66]. In such optimization problem, we applied dual decomposition and the average consensus algorithm in order to minimize the system operation cost while satisfying a coupled balance constraint in a distributed manner. The outcome of that approach is appropriate as it emulates the centralized solution. The scenario-based optimization problem for the hourly economic dispatch is defined as:

$$\begin{aligned}\underset{P^s_{\ell,k+j|k}}{\text{minimize}}\ J_\ell(P_{\ell,k+j|k},\boldsymbol{\lambda}_k) = \sum_{s\in\mathcal{S}} p_s \sum_{j=0}^{H_p} \Bigg\| \frac{\partial C(P^s_{\ell,k+j|k})}{\partial P^s_{\ell,k+j|k}} \\ - \lambda^s_{k+j} - \psi^{1,s}_{\ell,k+j} + \psi^{2,s}_{\ell,k+j} - \psi^{3,s}_{\ell,k+j} + \psi^{4,s}_{\ell,k+j} \Bigg\|^2,\end{aligned} \tag{5.7a}$$

subject to

$$P^{\min,s}_{\ell,k+j} \le P^s_{\ell,k+j|k} \le P^{\max,s}_{\ell,k+j}, \tag{5.7b}$$

$$\Delta P^{\min,s}_{\ell,k+j} \le \Delta P^s_{\ell,k+j|k} \le \Delta P^{\max,s}_{\ell,k+j}, \tag{5.7c}$$

$$0 \le \psi^{1,s}_{\ell,k+j}, \psi^{2,s}_{\ell,k+j}, \psi^{3,s}_{\ell,k+j}, \psi^{4,s}_{\ell,k+j}, \tag{5.7d}$$

$$0 = \psi^{1,s}_{\ell,k+j}\left(P^{\min,s}_{\ell,k+j} - P^s_{\ell,k+j|k}\right), \tag{5.7e}$$

$$0 = \psi^{2,s}_{\ell,k+j}\left(P^s_{\ell,k+j|k} - P^{\max,s}_{\ell,k+j}\right), \tag{5.7f}$$

$$0 = \psi^{3,s}_{\ell,k+j}\left(\Delta P^{\min,s}_{\ell,k+j} - \Delta P^s_{\ell,k+j|k}\right), \tag{5.7g}$$

$$0 = \psi^{4,s}_{\ell,k+j}\left(\Delta P^s_{\ell,k+j|k} - \Delta P^{\max,s}_{\ell,k+j}\right), \tag{5.7h}$$

where Lagrange multipliers are calculated for each scenario by using the dual decomposition and average consensus algorithms, which are detailed in [66].

• Ultra-short term economic dispatch: the following formulation for the distributed stochastic optimization problem is based on the distributed deterministic formulation proposed in [67]. The ultra-short term economic dispatch looks for maximizing the net profit of generators while balance is achieved. In order to achieve balance without an explicit coupled constraint, we proposed different algorithms for conventional generators.

The algorithms calculate an auxiliar variable in terms of active ramp-rate constraints and include it in the objective function. The entire process of the ultra-short term dispatch can be found in [67]. The scenario-based approach of that optimization problem is defined as:

$$\underset{P^s_{\ell,k+j|k}}{\text{minimize}} \sum_{s\in\mathcal{S}} p_s \sum_{j=0}^{H_p} \left\| \pi^s_{k+j} - \frac{\partial C_\ell(P^s_{\ell,k+j|k})}{\partial P^s_{\ell,k+j|k}} - \Psi^s_{\ell,k+j} \right\|^2, \tag{5.8a}$$

subject to

$$P^{\min,s}_{\ell,k+j} \leq P^s_{\ell,k+j|k} \leq P^{\max,s}_{\ell,k+j}, \tag{5.8b}$$

$$\Delta P^{\min,s}_{\ell,k+j} \leq \Delta P^s_{\ell,k+j|k} \leq \Delta P^{\max,s}_{\ell,k+j}. \tag{5.8c}$$

• Microgrid elements: in [67], we defined the deterministic behavior of different participants in a microgrid. Since renewable resources, price, and demand are uncertain variables, it is necessary to describe the optimization problem of distributed resources as stochastic programs. First, the scenario-based optimization problem for renewable resources is defined as:

$$\underset{P^s_{b,k+j|k}}{\text{maximize}} \sum_{s\in\mathcal{S}} p_s \sum_{j=0}^{H_p} \Big(\pi^s_{k+j} P^s_{b,k+j|k} - C_b(P^s_{b,k+j|k}) \Big), \tag{5.9a}$$

subject to

$$P^{\min,s}_{b,k+j} \leq P^s_{b,k+j|k} \leq P^{\max,s}_{b,k+j}, \tag{5.9b}$$

$$SOC^{\min,s}_b \leq SOC^s_{b,k+j|k} \leq SOC^{\max,s}_b, \tag{5.9c}$$

Second, the stochastic program for batteries operation is described by the following formulation:

$$\underset{P^s_{r,k+j|k}}{\text{maximize}} \sum_{s\in\mathcal{S}} p_s \sum_{j=0}^{H_p} \Big(\pi^s_{k+j} P^s_{r,k+j|k} - C_r(P^s_{r,k+j|k}) \Big), \tag{5.10a}$$

subject to

$$\hat{P}^{\min,s}_{r,k+j} \leq P^s_{r,k+j|k} \leq \hat{P}^{\max,s}_{r,k+j}, \tag{5.10b}$$

$$\Delta P^{\min,s}_{r,k+j} \leq \Delta P^s_{r,k+j|k} \leq \Delta P^{\max,s}_{r,k+j}, \tag{5.10c}$$

$$P^s_{r,k+j|k} \leq \frac{\tilde{D}_{k+j}}{n_r} \tag{5.10d}$$

Finally, the next stochastic optimization problem describes the combined operation of a renewable power plant and a battery, which enables arbitrage.

$$\underset{P^{r,s}_{u,k+j|k},P^{b,s}_{u,k+j|k}}{\text{maximize}} \sum_{s\in\mathcal{S}} p_s \sum_{j=0}^{H_p} (\pi^s_{k+j}(P^{r,s}_{u,k+j|k} + P^{b,s}_{u,k+j|k}) - C_u(P^{r,s}_{u,k+j|k}, P^{b,s}_{u,k+j|k})), \quad (5.11a)$$

subject to

$$\hat{P}^{r,\min,s}_{u,k+j} \le P^{r,s}_{u,k+j|k} \le \hat{P}^{r,\max,s}_{u,k+j}, \quad (5.11b)$$

$$\Delta P^{r,\min,s}_{u,k+j} \le \Delta P^{r,s}_{u,k+j|k} \le \Delta P^{r,\max,s}_{u,k+j}, \quad (5.11c)$$

$$P^{b,\min,s}_{u,k+j} \le P^{b,s}_{u,k+j|k} \le P^{b,\max,s}_{u,k+j}, \quad (5.11d)$$

$$SOC^{\min,s}_{u} \le SOC^{s}_{u,k+j|k} \le SOC^{\max,s}_{u}, \quad (5.11e)$$

$$P^{r,s}_{u,k+j|k} + P^{b,s}_{u,k+j|k} \le \frac{\tilde{D}_{k+j}}{n_r} \quad (5.11f)$$

5.4 Operation Coordination

In [66] and [67], we separately showed the performance of distributed approaches for solving the economic dispatch problem, i.e., the hourly and ultra-short term dispatch. From our analysis, we found that the trade-off between using hourly or ultra-short term dispatch is the computational time and the solution quality. Hourly dispatch obtains a better solution as it emulates the centralized dispatch that minimizes the system operation costs, whereas ultra-short term is faster but maximizes the profit of each agent. In order to enhance the solution quality, it is possible to combine both algorithms and exploit their advantages.

The combined operation architecture proposed here is based on some principles stated by Olivares et al. in [52], and the master slave configuration. Fig. 5.2 depicts the proposed architecture where the hourly dispatch is used as a master controller since it maximizes the global benefit. On the other hand, ultra-short term dispatch actuates as a slave controller, for it receives boundary conditions from hourly dispatch. Every hour the master dispatch finds optimal outputs for the current time k and next H_p hours. Meanwhile, the slave controller is executed between hours in order to track system changes (e.g., deviation of prices and renewables availability).

In master-slave configurations, a key factor is the information quality from the master controller and how this information is used by the slave controller. In the proposed

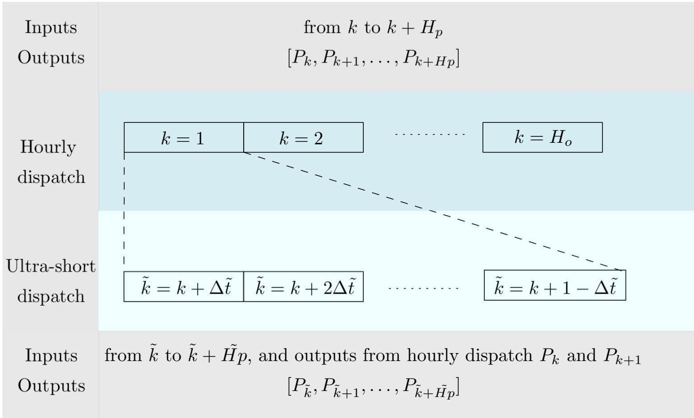


Fig. 5.2 Integrated operation of hourly and ultra-short term dispatch.

architecture, hourly dispatch provides two signals to ultra-short term controller, i.e., optimal outputs P_k and P_{k+1}. These signals are included as constraints in optimization problems, specially in the case of conventional generators. Case in point, P_k is the starting status of the system when ultra-short term dispatch is going to be executed, and P_{k+1} is the target output. This last signal is included as a boundary or termination constraint (TC) and must comply with ramp-rate limits. To better explain this scheme, see Fig. 5.3 where two different generation trajectories are depicted. First, P_k is the starting point of ultra-short term dispatch, i.e., ramp-rate limit must be respected ($\Delta P_{\tilde{k}}^{\min} \leq P_{k+\Delta\tilde{t}} - P_k \leq \Delta P_{\tilde{k}}^{\max}$). Second, the TC can be generally defined as $P_{k+1} + \Delta P_{\tilde{H}_p}^{\min} - \sigma_p \leq P_{\tilde{H}_p} \leq P_{k+1} + \Delta P_{\tilde{H}_p}^{\max} + \sigma_p$, which means that $P_{\tilde{H}_p}$ must lie on the region delimited by ramp-rate limits applied to P_{k+1}. Note that this region can be relaxed by including an additional variable σ_p, which represents the possible deviation of P_{k+1}, as it will be calculated with updated information when the slave controller finishes its operation. If the TC is not included in the combined operation, the slave controller will reach a solution P'_{H_p} that leads to an undesired output P'_{k+1} since conventional generators maximize profit in the ultra-short term dispatch.

5.5 Case study and results

5.5.1 Case study

In order to demonstrate the performance of distributed stochastic approaches, we use the NYISO load pattern along with some elements to form a microgrid. The example consists of three conventional generators, a wind generator without ESS, two solar panels (one with ESS and the other one without), and a stand-alone ESS. The

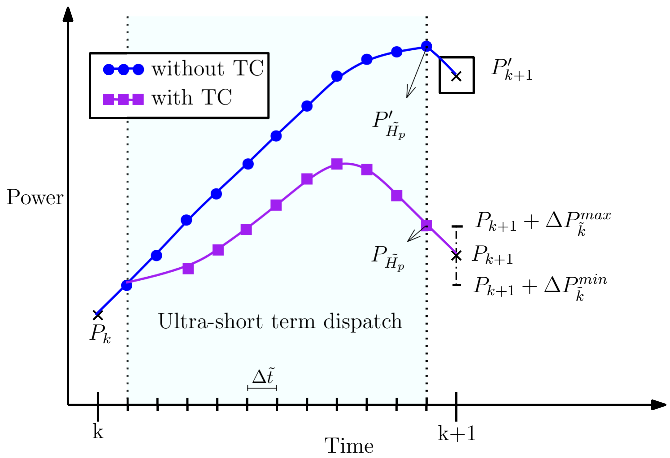


Fig. 5.3 impact of a termination constraint in the ultra-short term dispatch.

Table 5.1 Parameters of generators in the microgrid

Generator	a	b	$P^{\min}$	$P^{\max}$	$\Delta P^{\min}$	$\Delta P^{\max}$
	$[\frac{\$}{\mathrm{MW}^2}]$	$[\frac{\$}{\mathrm{MW}}]$	[MW]	[MW]	$[\frac{\mathrm{MW}}{5\mathrm{min}}]$	$[\frac{\mathrm{MW}}{5\mathrm{min}}]$
Conventional_1	0.5	1	0	8	-2	2
Conventional_2	1	10	0	8	-0.06	0.06
Conventional_3	7	35	0	10	-4	4
Wind + ESS	0	0.2	0	2.6	-2.6	2.6
PV	0	0.15	0	1.5	-1.5	1.5
PV	0	0.1	0	2.3	-2.3	2.3

Table 5.2 Parameters of ESS in the microgrid

Battery	b_ℓ $[\frac{\$}{\text{MW}}]$	$P^{\min}$ [MW]	$P^{\max}$ [MW]	$\text{SOC}^{\min}$ p.u.	$\text{SOC}^{\max}$ p.u.	P^{cap} [MW]
ESS	0.1	-0.167	0.167	0	1	1
ESS(Wind)	0.05	-0.84	0.084	0	1	2

magnitude of NYISO load pattern is scaled down for simulating a microgrid demand for 1-hour and 5-minute periods. Specifications of the generators and ESS in the microgrid are shown in Tables 5.1 and 5.2, respectively. The case study is very similar to the example proposed in Chapter 4. This simulation case shows how the hourly and ultra-short term approaches behave in terms of costs when uncertainty is considered while complying with ramp-rate constraints of generators.

In this chapter, uncertainty is associated to energy price, availability of renewable resources, and demand. In order to generate scenarios through the data-driven approach, it is possible to use historical data regarding absolute values of uncertain variables or their relative value (forecast error). We use this last one in the simulations as we can model forecast deviations and generate synthetic data with a normal distribution.

5.5.2 Results and discussion

The economic dispatch approaches proposed in [66] and [67] does not consider uncertainty in the optimization problems. However, it is necessary to take into account randomness of price, resources availability, and demand for enhancing efficiency. In order to show the effectiveness of stochastic programming by applying scenario generation to those optimization problems (formulations (5.7), (5.8), (5.9), (5.10), and (5.11)), we develop Montecarlo simulations for different configurations, i.e., Montecarlo realization parameters (μ_M and σ_M). In this section, results for the hourly dispatch, ultra-short term dispatch, and the integrated approach with a termination constraint are provided.

B.1 Hourly economic dispatch

Results of the hourly economic dispatch for both deterministic and stochastic approaches are provided in Fig. 5.4 and Table 5.3. In this case, the prediction horizon is set to 3 and three scenarios are considered for each stage. That is, a total of 27 scenarios are obtained through the data-driven scenario generation. We have verified the convenience of using this configuration by increasing the amount of scenarios with no significant reductions of operation costs. Fig. 5.4 shows the operation costs histogram obtained from a Montecarlo simulation with realization parameters $\mu_M = 0\%$

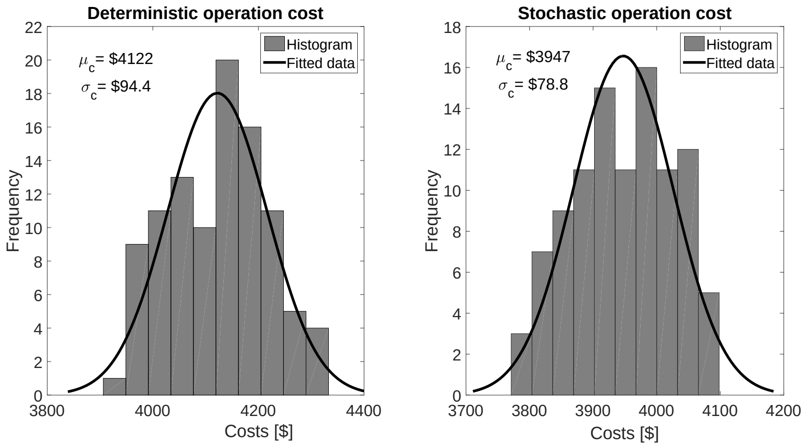


Fig. 5.4 Histogram and data fitting for a Montecarlo simulation with realization parameters $\mu_M = 0$ and $\sigma_M = 3$ when is historical data error has parameters $\mu_d = 0$ and $\sigma_d = 3$ for the hourly dispatch.

Table 5.3 Montecarlo results for different realization scenarios when historical error data has parameters $\mu_d = 0\%$ and $\sigma_d = 3\%$ for the hourly dispatch.

Montecarlo scenario		Deterministic		Stochastic	
		μ_c	σ_c	μ_c	σ_c
$\mu_M = 0$	$\sigma_M = 3$	4122.31	94.4	3947.42	78.81
$\mu_M = 0$	$\sigma_M = 5$	4186.02	155.39	4000.07	136.71
$\mu_M = 0$	$\sigma_M = 10$	4421.90	317.71	4224.89	274.38
$\mu_M = 3$	$\sigma_M = 3$	4498.53	119.45	4299.75	111.04
$\mu_M = 3$	$\sigma_M = 5$	4542.24	175.65	4340.42	156.59
$\mu_M = 3$	$\sigma_M = 10$	4797.98	352.96	4571.81	313.291

and $\sigma_M = 3\%$ for the forecast error when historical data has the same distribution parameters. From the histogram result, we fit these data to a normal distribution function in order to obtain statistical parameters. Results show that the stochastic approach performs better since its mean and standard deviation ($\mu_c = \$3947$ and $\sigma_c = \$78.8$) are lower than those obtained with the deterministic approach ($\mu_c = \$4122$ and $\sigma_c = \$94.4$).

In addition, Table 5.3 and Fig. 5.5 show Montecarlo operation costs for different realization scenarios when historical error data has parameters $\mu_d = 0\%$ and $\sigma_d = 3\%$. In every realization scenario the stochastic approach performs better than the deterministic approach even if the realization parameters are different from historical error parameters (e.g., $\mu_M = 3$ and $\mu_d = 0$). The cost difference of both approaches is $197.4 in average. Moreover, the operation cost mean increases as forecast error increases, i.e., when μ_M and σ_M are larger. Another benefit of using stochastic

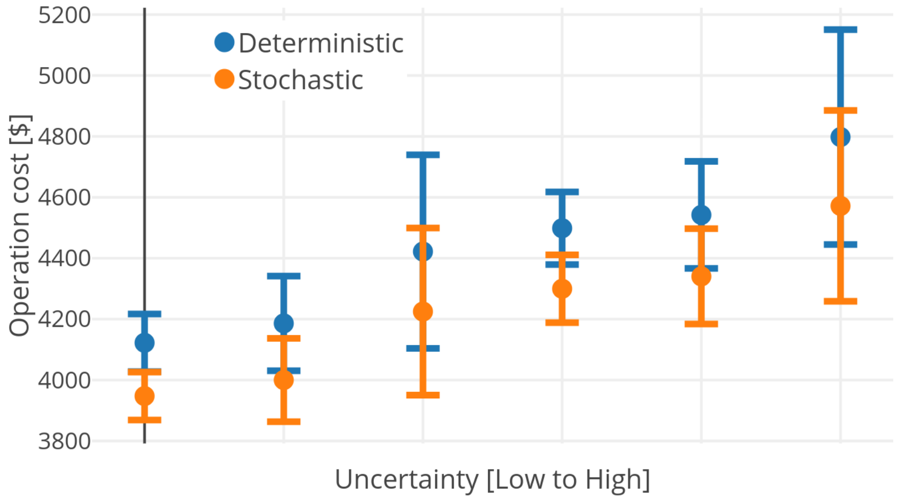


Fig. 5.5 Operation cost for different Montecarlo simulations when historical data error has parameters $\mu_d = 0\%$ and $\sigma_d = 3\%$ for the hourly dispatch.

programming is that the standard deviation obtained is shorter than that obtained with the deterministic approach for every scenario considered. From these results it can be verified that stochastic optimization through the data-driven scenario generation is appropriate for solving the hourly economic dispatch under uncertainty.

B.2 Ultra-short term dispatch

Results of the ultra-short term economic dispatch for both deterministic and stochastic approaches are provided in Fig. 5.6 and Table 5.4. As in the previous case, the prediction horizon is set to 3 and three scenarios are considered for each stage. We have verified as well that with more scenarios there are no significant reductions of operation costs and the computational time increases. This configuration depends on the case study features and uncertain variables. Fig. 5.6 shows the operation costs histogram obtained from a Montecarlo simulation with realization parameters $\mu_M = 0\%$ and $\sigma_M = 3\%$ for the forecast error when historical data has the same distribution parameters. We found statistical parameters of these results by fitting them to a normal distribution function. From the obtained parameters we can verify that the stochastic approach performs better because its mean ($\mu_c = \$5443$) is lower than that obtained with the deterministic approach ($\mu_c = \$5687$).

In addition, Table 5.4 and Fig. 5.7 show Montecarlo operation costs for different realization scenarios when historical error data has parameters $\mu_d = 0\%$ and $\sigma_d = 3\%$. For each realization scenario the stochastic approach performs better than the deterministic approach even if the realization parameters largely differ from historical

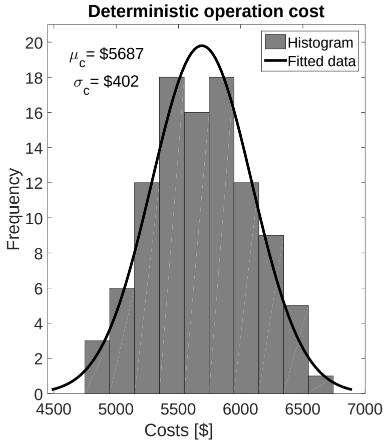


Fig. 5.6 Histogram and data fitting for a Montecarlo simulation with realization parameters $\mu_M = 0$ and $\sigma_M = 3$ when is historical data error has parameters $\mu_d = 0$ and $\sigma_d = 3$ for the ultra-short term dispatch.

Table 5.4 Montecarlo results for different realization scenarios when historical error data has parameters $\mu_d = 0\%$ $\sigma_d = 3\%$ for the ultra-short term dispatch.

Montecarlo scenario		Deterministic		Stochastic	
		μ_c	σ_c	μ_c	σ_c
$\mu_M = 0$	$\sigma_M = 3$	5687.78	402.06	5443.60	417.46
$\mu_M = 0$	$\sigma_M = 5$	5671.15	373.24	5454.37	401.61
$\mu_M = 0$	$\sigma_M = 10$	5862.52	547.43	5646.54	528.51
$\mu_M = 3$	$\sigma_M = 3$	5867.10	403.99	5541.69	425.91
$\mu_M = 3$	$\sigma_M = 5$	6090.32	436.09	5807.87	466.57
$\mu_M = 3$	$\sigma_M = 10$	6483.30	681.64	6195.49	656.59

error parameters (e.g., $\sigma_M = 10$ and $\sigma_d = 3$). The cost difference of both approaches is \$262.1 in average. Moreover, the operation cost mean increases as forecast error increases, i.e., when μ_M and σ_M are larger. In this type of dispatch, the standard deviation has no tendency as it is larger in the stochastic approach for some cases. From these results it can be verified that using the data-driven scenario generation for considering uncertainty in the optimization problem is appropriate in the ultra-short term dispatch. Even though the stochastic approach performs very good, costs in the ultra-short term dispatch are higher (Table 5.4) than those obtained with the hourly dispatch (Table 5.3). This result was expected as the hourly dispatch emulates a centralized approach that minimizes operation costs whereas ultra-short term is a faster method that does not optimize the social benefit.

B.3 Integrated dispatch

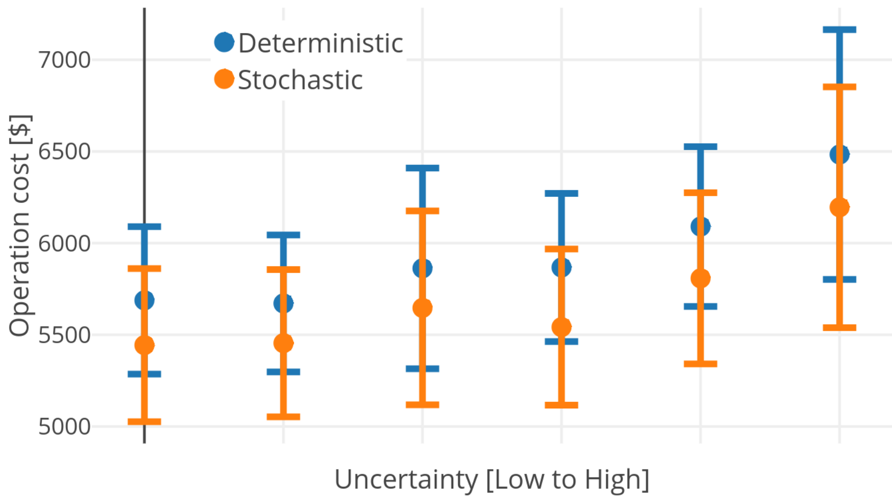


Fig. 5.7 Operation cost for different Montecarlo simulations when historical data error has parameters $\mu_d = 0\%$ and $\sigma_d = 3\%$ for the ultra-short term dispatch.

This section shows results of integrating both the hourly and ultra-short term dispatch under a master-slave configuration with a termination constraint. On one hand, prediction horizon for the hourly dispatch is set to 3 and three scenarios are considered for each stage. On the other hand, prediction horizon of ultra-short term is set to 10 and two scenarios are considered for the first three stages. Prediction horizon in the ultra-short term is reduced according to the shrinked horizon strategy proposed in [52]. Fig. 5.8 depicts the cumulative operation cost for the integrated dispatch with and without a termination constraint, and Montecarlo benefits of using this kind of restriction. Cumulative operation cost shows that lower costs are obtained when ultra-short term and hourly dispatch share information. Moreover, benefits histogram (defined as the cost difference between coordinated and non-coordinated dispatch) shows that it is more likely to obtain benefits when using a termination constraint (benefits mean is $\mu_b = 147.36$). Table 5.5 shows Montecarlo costs for different realization scenarios when solving the economic dispatch with different configurations. Configurations are defined as follows: A) deterministic approach without TC, B) deterministic approach with TC, C) stochastic MPC without TC, and D) stochastic dispatch with TC. These results are also shown in Figs. 5.9 and 5.10. From the results, it can be seen that when realization parameters are small ($\mu_M = 0\%$ and $\sigma_M = 3\%$) , the behavior of the system is better when solving a deterministic approach. However, as uncertainty increases in the system, it is preferable to use stochastic approaches

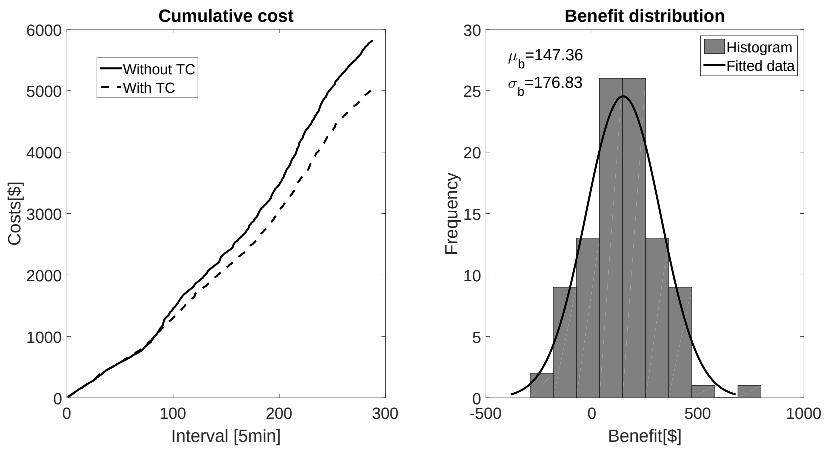


Fig. 5.8 Cumulative cost, benefit histogram, and data fitting for a Montecarlo simulation with realization parameters $\mu_M = 3$ and $\sigma_M = 10$ when is historical data error has parameters $\mu_d = 3$ and $\sigma_d = 10$ for the integrated dispatch.

along with a coordination scheme. This effect is enforced if parameters of historical data are smaller or equal to those of the Montecarlo realization.

In addition, Table 5.6 demonstrate Montecarlo benefits for different realization scenarios when historical error data has parameters $\mu_d = 3\%$ and $\sigma_d = 10\%$ for four cases. Considered cases are: i) deterministic comparison of taking into account the termination constraint, ii) stochastic comparison of considering the boundary restriction, iii) deterministic versus stochastic without TC, and iv) deterministic versus stochastic with TC. Stochastic benefits (deterministic cost minus stochastic cost) are shown as well in Figs. 5.11 and **??** First, from results it can be seen that mean of benefits is always positive for the first case, i.e., operation costs are lower when applying a TC. Second, the effect of a TC in the stochastic approach is positive if system behavior is similar to historical data. Third, the effect of using a stochastic approach instead of one deterministic is positive if system behavior is similar to historical data. Fourth, even though the deterministic dispatch obtains better results in comparison with the stochastic approach when a TC is considered, the effect is contrary if historical data is similar to Montecarlo realizations (i.e., $\mu_d = 0$, $\sigma_d = 3$). Furthermore, if more scenarios are considered in the ultra-short term dispatch (e.g., 3 instead of 2), the stochastic approach obtains better costs results to the detriment of computational time.

Table 5.5 Montecarlo costs results for different realization scenarios when historical error data has parameters $\mu_d = 3\%$ $\sigma_d = 10\%$ for four cases.

	$\mu_M = 0\%,\ \sigma_M = 3\%$		$\mu_M = 0\%,\ \sigma_M = 10\%$		$\mu_M = 3\%,\ \sigma_M = 10\%$	
	μ_c	σ_c	μ_c	σ_c	μ_c	σ_c
A	4619.60	33.48	5118.00	106.48	5601.40	125.02
B	4536.60	30.36	4919.40	107.75	5454.00	135.06
C	4624.10	34.12	5114.50	107.30	5597.80	124.17
D	4643.7	28.28	5014.60	97.64	5471.10	131.85

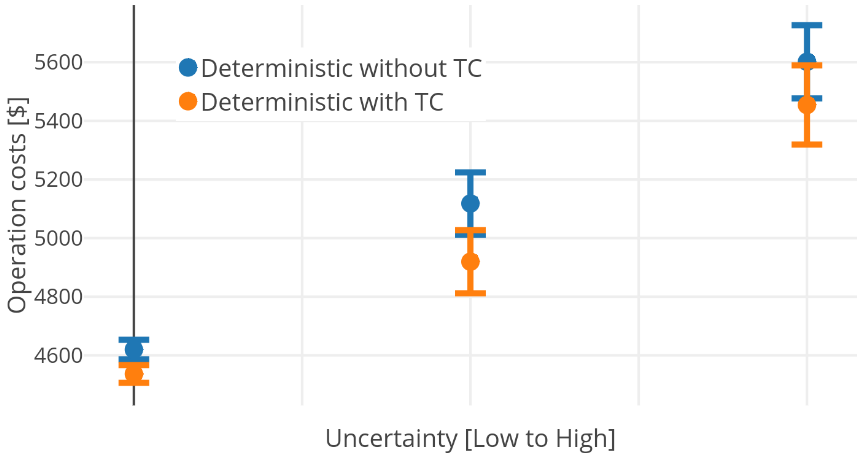


Fig. 5.9 Deterministic comparison with parameters $\mu_d = 3\%$ and $\sigma_d = 10\%$.

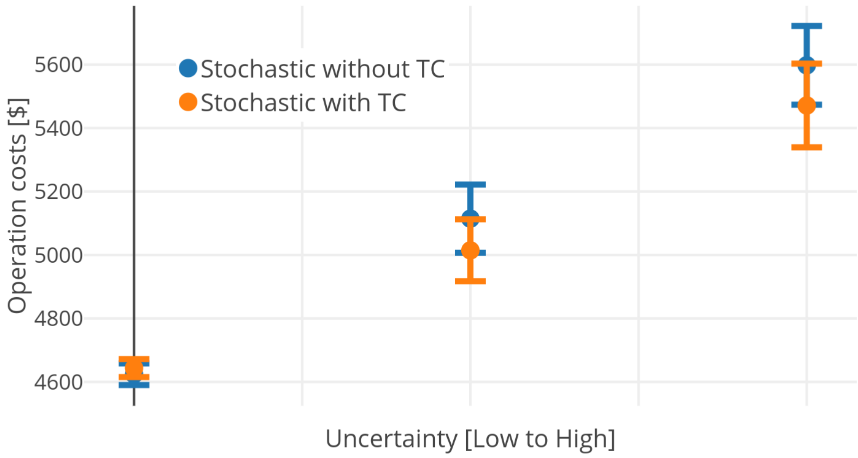


Fig. 5.10 Stochastic comparison with parameters $\mu_d = 3\%$ and $\sigma_d = 10\%$.

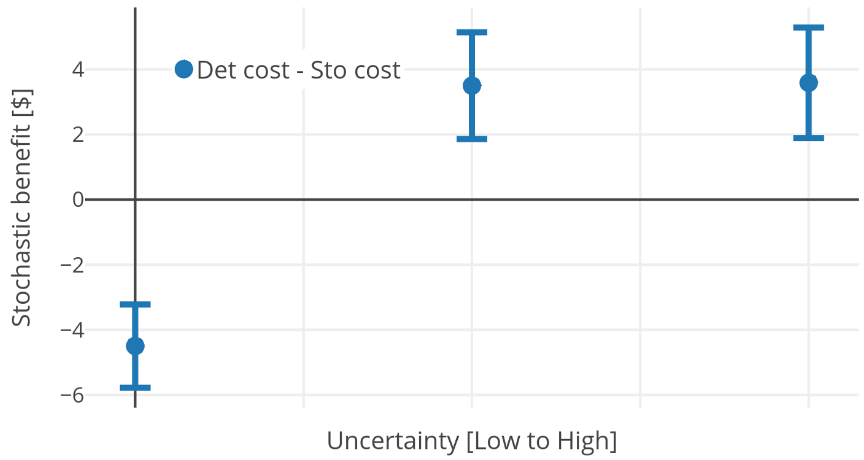


Fig. 5.11 Stochastic benefit without TC with parameters $\mu_d = 3\%$ and $\sigma_d = 10\%$.

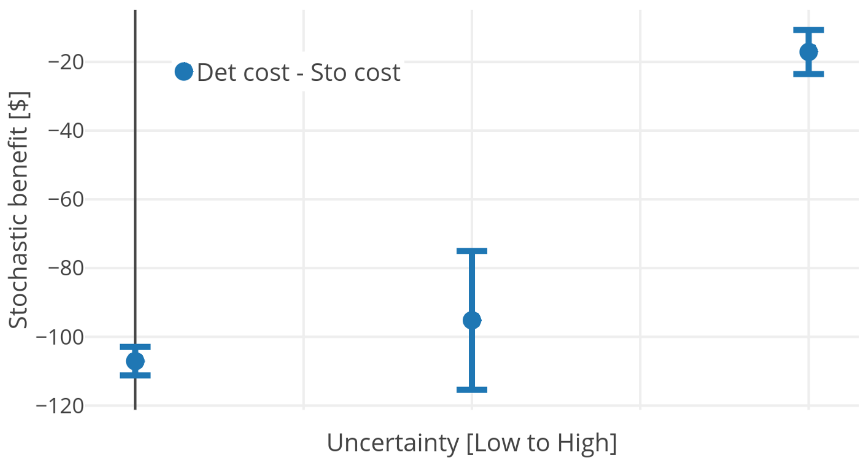


Fig. 5.12 Stochastic benefit with TC with parameters $\mu_d = 3\%$ and $\sigma_d = 10\%$.

Table 5.6 Montecarlo benefits results for different realization scenarios when historical error data has parameters $\mu_d = 3\%$ $\sigma_d = 10\%$ for four cases.

	$\mu_M = 0\%,$	$\sigma_M = 3\%$	$\mu_M = 0\%,$	$\sigma_M = 10\%$	$\mu_M = 3\%,$	$\sigma_M = 10\%$
	μ_b	σ_b	μ_b	σ_b	μ_b	σ_b
1	83.00	46.19	198.65	157.61	147.36	176.83
2	-19.63	45.15	99.95	146.05	126.69	175.88
3	-4.47	8.48	3.51	8.37	3.60	11.37
4	-107.11	8.11	-95.19	144.25	-17.06	16.77

5.6 Concluding Remarks

A data-driven scenario generation method has been integrated within distributed economic dispatch approaches in order to address uncertainty of power systems operation. The method find scenarios that accurately represent variables uncertainty by minimizing error of statistical properties with respect to historical data. Stochastic programming has been applied to the hourly and ultra-short term economic dispatches for considering price, demand, and resources randomness.

We proposed as well a master-slave configuration by including a termination constraint in the ultra-short term dispatch. This configuration allows the system operator to obtain better costs in real-time operation. We have implemented a shrinked horizon MPC to effectively coordinate both the hourly and ultra-short term approaches. As future work we plan to deeply analyze coordination of these two methods under a stochastic programming framework.

Chapter 6

Concluding remarks and contributions

From the work developed in this doctoral thesis several conclusions and contributions can be drawn. In the first chapter, research questions that motivated this work were described. These questions represent the main objectives of this document and are associated to concluding remarks.

The operation of some elements of smart grids was explored and analyzed in order to include them in power systems operation. Even though several authors tend to discount renewable energy from demand, we have defined it as a decision variable. this feature allows renewable generators to balance the power system demand and to arbitrage if they have energy storage systems. Energy storage systems have been defined as agents that arbitrage the market as a function of the energy market price. In this sense, we have provided a general characterization of these elements without limiting the use to a specific technology. As a future work in this matter, we are looking forward to include demand response programs within the proposed energy management systems.

We explored what method is appropriate for solving economic dispatch problems under the new framework of smart grids and renewable resources. Since economic dispatch and unit commitment have been usually solved with heuristic algorithms, linear and non-linear programming, Lagrangian relaxation, among others, we analyzed other methods and decided to use model predictive control. MPC methods were more commonly applied to industrial applications than power systems. Such applications in power systems have been intensified within the last few years because of the integration of distributed generation technologies such as roof-top solar panels and local microgrids. Traditionally, the economic dispatch problem has been addressed with approaches that pre-compute (off-line) in open-loop an optimal solution for an interval, e.g., the day ahead dispatch. However, with the presence of more disturbances in the system due to the stochastic nature of renewable resources, off-line open-loop methods have lost efficiency and accuracy. One alternative is to implement stochastic approaches for considering uncertainty in the system, but the optimal solution is still computed off-line in open-loop for most methods, and an on-line feedback policy is very difficult or impossible to obtain, especially in the presence of inter-temporal constraints. On the other hand, the MPC method solves an open-loop finite-horizon control problem on-line for the current state of the system. After new measurements and information of the system are available, a new open-loop finite-horizon optimization problem with measured initial conditions is computed. Here, forecast information of stochastic variables is used for finding the optimal solution in the current state. When new measures of stochastic variables is available, a new finite-horizon forecast can be obtained, thus increasing information accuracy. For such reasons, the MPC is known as an on-line closed-loop method that mitigates the issue of variability and uncertainty, and its response to large disturbances improves if it is combined with stochastic methods. In addition, MPC handling of constraints is very attractive since it considers the impact of future conditions in the present operation, and several types of constraints can be included.

By using the MPC concept, we proposed a distributed economic dispatch that meets a dynamic load while complying with ramp-rate limits. The main contribution on this topic is the method's ability to minimize operation costs in a distributed manner. The proposed iterative approach emulates the traditional centralized dispatch without sharing any private information such as generators' costs and capacities. Here, generators share information by using an average consensus algorithm and maximizes global benefit through a dual-decomposition formulation. Even though the proposed approach is iterative, it is feasible for hourly and short-term periods, and depending on the power system characteristics it might be feasible for ultra-short term dispatch. The average convergence rate is 200 iterations. With this MPC-based method, the operator is able to keep tracking of the system variables and to maintain generation dispatch close to optimal theoretical set-points.

In order to obtain an economic dispatch method feasible for ultra-short term operation, we proposed a novel approach that accounts for optimal operation of power systems while ramp-rate limits are addressed. Balance of energy is attained through price signal given by the system operator. Balance of energy is achieved by conventional generators which use novel algorithms that identify enforced ramps and comply with the system security. Balance of energy is fulfilled even though generators pursue their own benefit maximization. In addition, generators do not share any private information with other agents. Furthermore, renewable generators are able to balance energy of the system, especially when sum of renewable resources availability is larger than load. Since DDMPC might not be feasible for the ultra-short term dispatch because of decision variables amount, computational requirements, and number of iterations, and intra-hour dispatch is being more relevant for current smart grids, the speed and efficiency of DMPC become critical contributions of this research. Moreover, formulation of elements commonly used in microgrids has been included. First, renewable power plants have been considered and defined as generator-only and generator with energy storage system, which are able to balance the microgrid. Second, stand-alone energy storage systems have been defined with arbitrage capabilities for maximizing net profit.

As it has been highlighted throughout the research, uncertainty is a critical feature of the new smart grid concept and renewable resources. From different methods analysis we decided to use and explore stochastic programming through scenario generation. Because several existing algorithms for creating scenarios rely on distribution information, which is very complex to obtain, we have implemented a data-driven scenario generation that takes into account not only the moment matching problem but the distribution matching problem as well. This method was successfully applied to the multi-stage MPC-based economic dispatch problems, where uncertainty has been linked to energy price, renewable availability, and load. From the results, we verified that stochastic programming along with MPC performs better than deterministic MPC in uncertain environments.

Because the ultra-short term dispatch DMPC is faster than DDMPC but its solution is not optimal from a social point of view, we have proposed a hierarchical architecture to enhance the power system performance. In this architecture, the DDMPC functions as a master controller that gives optimal hourly signals to the DMPC. The DMPC performs every 5 minutes by taking into account boundary conditions given by the DDMPC. This structure enhances the system operation cost with low computational burden.

To sum up, in this doctoral thesis we have the following contributions: i) verification of MPC as an appropriate method for solving the economic dispatch problem, ii) identification and modeling of some (renewable with and without ESS, and energy storage systems) for distributed operation, iii) design of an MPC-based distributed economic dispatch that emulates a centralized approach without sharing any private information and feasible for short-term and hourly periods, iv) design of an MPC-based distributed economic dispatch that is feasible for ultra-short term and complies with ramp-rate limits through novel algorithms, v) stochastic-distributed MPC-based methods for the economic dispatch problem that are feasible for hourly and ultra-short term, and vi) hierarchical architecture that enhances system operation costs by combining advantages of both DDMPC and DMPC through boundary constraints.

We have addressed several topics in this thesis, as it has been summarized above. However, there are still open questions that can be addressed in future work. First, demand response behavior must be included in the proposed economic dispatch problems. Specifically, we encourage to begin the analysis by modeling a price responsive demand. Second, we have verified that a hierarchical architecture of DDMPC and DMPC improves the system performance. Nevertheless, we believe that integration of both approaches can be analyzed and improved while maintaining feasibility. Third, the issue of network constraints must be addressed. We believe that a first approach could consider an additional optimization problem that finds a neighboring solution to that obtained with DDMPC and DMPC. Fourth, the ongoing research on smart grids shows that several microgrids might be installed in the same feeder. In this sense, a multigrid dispatch model can be used to enhance the system performance and take advantage of possible synergies. Finally, the proposed methods may be extended to some other applications an not only economic dispatch problem.

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