Sapienza Università di Roma

Integrating scheduling process for Italian ancillary services and balancing markets, considering uncertainties of RES-based DG.

University of Rome "La Sapienza"
Engineering and Applied Science for Energy and Industry (XXXV cycle)

Stefano Panella
ID number 1537427

Advisor
Prof. Maria Carmen Falvo

Co-Advisors
Eng. Mauro Caprabianca
Eng. Federico Quaglia

Academic Year 2023/2024

Thesis defended on 27th April 2023
in front of a Board of Examiners composed by:

Prof. Paola Verde (chairman)
Prof. Alberto Prudenzi
Prof. Roberto Faranda

Integrating scheduling process for Italian ancillary services and balancing markets, considering uncertainties of RES-based DG.
PhD thesis. Sapienza University of Rome

This thesis has been typeset by LaTeX and the Sapthesis class.

Author's email: stefano.panella@uniroma1.it

Abstract

The proliferation and diffusion of Renewable Energy Systems (RESs), along with their associated uncertainties, have had an impact on the management of electrical grids and electricity markets. The focus of my doctoral thesis, carried out in collaboration with the Italian Transmission Operator (TSO) Terna, was on studying how the impact of RESs on the national transmission grid could be contained by reviewing the rules of the electricity market and the management of conventional thermal power plants.

The main issue examined was whether it was possible to devise a new algorithm for ancillary markets to better manage the evolution of RESs. The presence of RESs necessitates the implementation of measures for integrating scheduling processes for ancillary services and balancing markets, taking into account the uncertainties of RESs.

To achieve this goal, a comprehensive review of Optimum Power Flow (OPF) algorithms was conducted. Subsequently, a Projected Assessment of System Adequacy (PASA) simulation was carried out using the PLEXOS software to analyze how solar and wind generation could impact the choice of scheduling maintenance for conventional thermal power plants.

This manuscript is divided into five sections and one appendix. The Introduction will provide an overview of the current state of the Italian electrical grid, outlining the different interconnections between Italy and neighboring countries and anticipating the main challenges that RESs could introduce into the operation of the electrical grid. In Section 2, titled "The power flow algorithms in electricity markets", the problem under consideration will be introduced by providing a description of the Italian electricity market. Section 3, titled "The state of art about the Optimum Power Flow algorithms", will analyze the current state of OPF algorithms, distinguishing between classic OPF problems and stochastic OPF methods. Section 4, titled "Projected Assessment of System Adequacy (PASA)", will describe the PASA simulation, how the model was implemented, and the results will be presented in Section 5, titled "PASA simulation results".

Finally the "Other research activities" writes in appendix will illustrate the parallel activities that I have been conducted during this three year of work.

Contents

List of Acronyms

AC	Alternate Current
ACOPF	Alternate Current Optimal Power Flow
aFRR	automatic Frequency Restoration Reserve
ARERA	Autorità di Regolazione per Energia Reti e Ambiente
AUX	Auxiliaries
BB	Breeding Blanket
BD	Bender Decomposition
BoP	Balance of Plant
BUI	Buildings
CCO	Chance Constrained Optimization
CRIDA	Complementary Regional Intra-Day Allocation
CRYO	Cryoplant and Cryodistribution
CZC	Cross Zonal Capacity
DC	Direct Current
DCOPF	Direct Current Optimal Power Flow
DEMO	DEMOnstration Power Plant
DFC	Dynamic Flow Controller
DIA	Diagnostics
DPFC	Dynamic Power Flow Controller
EBGL	Guideline on Electricity Balancing
ED	Economic Dispatch
ELL	Electrical Load List
FACTs	Flexible AC Transmission Systems

GME Gestore dei Mercati Energetici

GBD Generalized Bender Decomposition

HCD Heating and Current Drive

HCPB Helium Cooled Pebble Bed

HCPB ICD BOP Helium Cooled Pebble Bed Indirect Coupling Design Balance of Plant

HVDC High Voltage Direct Current

HVDC B2B HVDC Back to Back

HVN High Voltage Network

IP Investment Protection

IPM Interior Point Method

ITER International Thermonuclear Experimental Reactor

LOLE Loss of Load Expectation

LOLP Loss of Load Probability

LP Linear Programming

LR Lagrangian Relaxation

MAG Magnet System

MARI Manually Activated Reserves Initiative

MB Mercato del Bilanciamento

MCO Continuous Trading Matching Algorithm

mFRR manual Frequency Restoration Reserve

MGP Mercato del giorno Prima

MI Mercato Infragiornaliero

MILP Mixed Integer Linear Program

MINLP Mixed Integer Non-Linear Program

MLVN Medium and Low Voltage Network

MPE Mercato a Pronti dell'Energia

MSD Mercato del Servizio di Dispacciamento

MTE Mercato a Termine dell'energia

MTTR	Generator Mean Time to Repair
MTU	Market Time Unit
NECPs	National Energy and Climate Plans
NEMO	Nominated Electricity Market Operator
NLP	Nonlinear Programming
NP	Nondeterministic Polynomial-time
NTC	Net Transfer Capacity
OA	Outer Approximation
OL	Ordinary Load
OPF	Optimum Power Flow
PASA	Projected Assessment of System Adequacy
PCS	Plant Control System
PES	Plant Electrical System
PICASSO	Platform for the International Coordination of Automated Frequency Restoration and Stable System Operation
POD	Point Of Delivery
PUN	Prezzo Unico Nazionale
QP	Quadratic Programming Relaxation
RESs	Renewable Energy Systems
RM	Remote Maintenance System
RO	Robust Oprimization
RR	Replacement Reserve
SCUC	Security Constrained Unit Commitment
SCUCED	Security Constrained Unit Commitment and Economic Dispatch
SDP	Semidefinite Programming Relaxation
SIC	Safety Important Classified
SIDC	Single Intra-Day Coupling
SOCP	Second-Order Cone Programming Relaxation
SP	Stochastic Programming

SSSC	Static Synchronous Series Compensator
STATCOM	Static Synchronous Compensator
SVC	Static VAR Compensator
SW	Social Welfare
TCSC	Thyristor Controlled Series Compensator
TER.HCPB	Helium Cooled Pepple Bed
TERRE	Trans European Replacement Reserves Exchange
TER.WCLL	Water Cooled Lithium Lead
TFV	Tritium, Fueling, Vacuum
THD	Total Harmonic Distortion
TLOP	Probability of Transmission Line Overload Accepted
TSO	Transmission Operator
UC	Unit Commitment
UCED	Unit Commitment and Economic Dispatch
UPFC	Unified Power Flow Controller
VREs	Variable Renewable Energy Sources
VV	Vacum Vessel
WCLL	Water Cooled Lithium Lead
WCLL DCD BOP	Water Cooled Lithium Lead Direct Coupling Design Balance of Plant
XBID	Cross Border Intra-Day

Chapter 1

Introduction

The ecological transition represents a significant change for the Italian electrical grid. The scientific community commonly acknowledges that climate change is closely related to human activities, as evidenced by the global temperature rising by approximately 1 °C since the end of the 19th century. Article 2 of the Paris Agreement [1] outlines a global framework to prevent dangerous climate change, which includes the following objectives:

- ensuring that the global average temperature increase remains well below 2 °C above pre-industrial levels, while also striving to limit the temperature increase to 1.5 °C above pre-industrial levels, as this would significantly decrease the risks and impacts of climate change.
- enhancing the ability to adapt to the adverse effects of climate change, while also fostering climate resilience and developing low greenhouse gas emission strategies in a way that does not jeopardize food production.
- aligning financial investments with a low greenhouse gas emission and climate-resilient development pathway.

In accordance with Article 2 of the Paris Agreement, the European Union has approved National Energy and Climate Plans (NECPs) aimed at reducing CO_2 emissions by at least 55 % by 2030. To achieve this goal, investments in Renewable Energy Systems (RESs) are necessary. The main objectives of the Italian NECPs are as follows [2]:

- achieving a 30 % share of energy from RESs in gross final energy consumption;
- achieving a 22 % share of energy from RESs in gross final energy consumption in the transport sector;
- reducing primary energy consumption by approximately 43 % compared to the PRIMES 2007 scenario;
- reducing greenhouse gas emissions by about 33 % for all non-Emissions Trading System sectors compared to 2005.

Table 1.1. List of the members countries of the Med-TSO since the "Mediterranean Master Plan II".

COUNTRY	TSO
Albania	OST
Algeria	SONELGAZ, GRTE, OS
Cyprus	TSOC
Croatia	HOPS
Egypt	EETC
France	RTE
Greece	ADMIE
Israel	IEC
Italy	TERNA
Jordan	NEPCO
Libya	GECOL
Morocco	ONEE
Montenegro	CGES
Palestine	PETL
Portugal	REN
Spain	REE
Slovenia	ELES
Tunisia	STEG
Turkey	TEIAS

To achieve its objectives, the Transmission Operator (TSO) named "Terna" considers all potential issues that could arise in the electrical grid, such as security, adequacy, service quality, resilience, and efficiency. Terna plans to avoid these problems through future investments, which include constructing new electrical lines to increase interconnections with neighbouring countries.

Italy's strategic geographical position in Europe and the Mediterranean sea makes it an ideal hub for the Mediterranean energy market. Italy could serve as a bridge to the Balkan, North European, West European, and African countries. Cooperation among Mediterranean TSOs is coordinated through the Med-TSO association, which aims to integrate and interact with the electrical grids of the various Mediterranean countries. Table 1.1 summarizes the member countries of the Med-TSO.

In pursuit of this objective, the "Mediterranean Master Plan 2020" [3] outlines the following key actions:

- developing Mediterranean scenarios;
- defining a list of future interconnection projects;
- creating reference models of power systems at the regional level to perform market studies.

1.1 The Italian electrical grid state of art

Terna is responsible for the ownership and management of the National electrical grid, which spans over 66 000 km and includes approximately 890 electrical substations. The grid is characterized by five voltage levels: 380 kV, 220 kV, 150 kV, 132 kV, and 60 kV. Tables 1.2 and 1.3 provide a summary of the current situation in Italy.

Table 1.2. A summary of the actual situation about the Italian electrical grid [4].

Voltage level	Air lines	Underground cables	Submarine cables
380 kV	11 726 km	274 km	1445 km
220 kV	9488 km	394 km	234 km
$\leq$ 150 kV	46 847 km	1597 km	83 km
Total	68 061 km	2265 km	1762 km

Table 1.3. Number of power transformers installed into the Italian electrical grid [4].

Voltage level	Substations	Power transformers	Power
380 kV	167	422	121 658 MVA
220 kV	150	215	34 003 MVA
$\leq$ 150 kV	580	132	4579 MVA
Total	887	759	160 240 MVA

In general, high voltage transmission lines consist of several voltage levels, which can be divided into two distinct groups. In the case of Italy, these two groups can be summarized as follows [5]:

- transmission grid: this group is characterized by 380 kV and 220 kV and represents the backbone of the Italian electrical grid. Its main function is to transfer high power throughout the entire nation.
- sub-transmission grid: this group is responsible for transferring power through three different voltage levels, namely 150 kV, 132 kV, and 60 kV.

Figure 1.1 (a) displays a geographical map of networks with voltage levels equal to or greater than 380 kV [6].

Additionally, the Italian electrical network is connected to foreign countries through 27 electrical interconnections, which consist of both submarine and overhead air lines that use AC and DC technology. These interconnections are summarized in Figure 1.1 (b). Due to Italy's strategic geographic location, the transfer capacity is concentrated at the northern border, making our country an ideal hub in the Mediterranean Sea.

The countries we are connected with are Switzerland (12), Austria (3), Slovenia (1), Montenegro (1), Greece (1), Malta (1), and France (7).

The import and export Net Transfer Capacity (NTC) are summarized in Table 1.4 and Table 1.5.

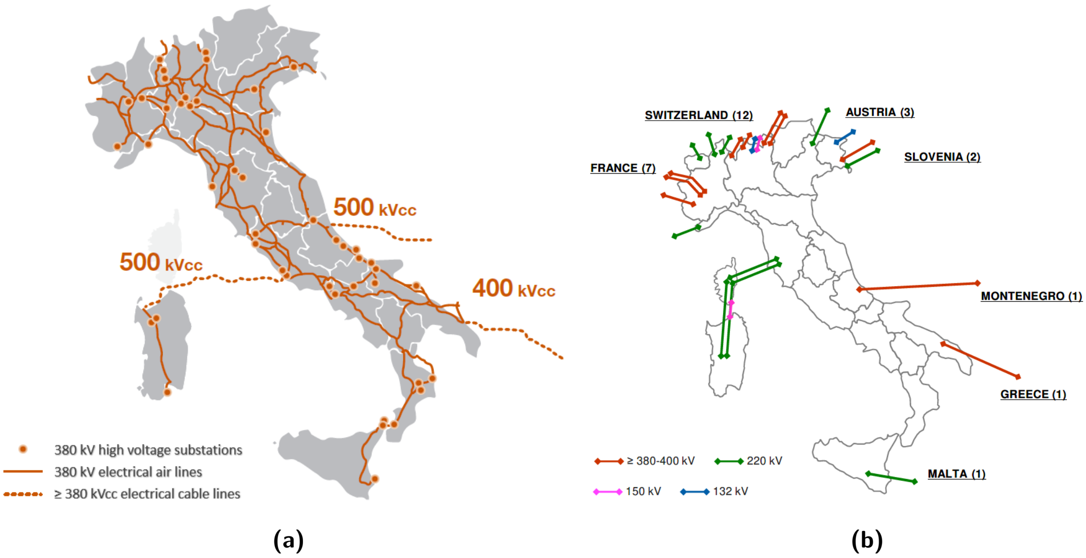


Figure 1.1. Map of the National Electrical Grid [6]: (a) The HV Italian electrical grid. (b) The HV interconnections between Italy and the other countries.

Table 1.4. Import Net Transfer Capacity between Italy and the foreign countries [6].

Period	Country	Winter [MW] Peak	Winter [MW] Off Peak	Summer [MW] Peak	Summer [MW] Off Peak
Monday-Saturday	France	3150	2995	2700	2470
	Switzerland	4240	3710	3420	3100
	Austria	315	295	270	255
	Slovenia	730	620	515	475
	Total Northern border	8435	7620	6905	6300
	Greece	500	500	500	500
	Montenegro	600	600	600	600
Sunday	France	3150	2995	2700	2470
	Switzerland	4240	3710	3420	3100
	Austria	315	295	270	255
	Slovenia	730	620	515	475
	Total Northern border	8435	7620	6905	6300
	Greece	500	500	500	500
	Montenegro	600	600	600	600

Table 1.5. Export Net Transfer Capacity between Italy and the foreign countries [6].

Period	Country	Winter [MW]		Summer [MW]	
		Peak	Off Peak	Peak	Off Peak
Monday-Saturday	France	995	1160	870	1055
	Switzerland	1810	1910	1440	1660
	Austria	100	145	80	100
	Slovenia	660	680	620	645
	Total northern border	3565	3895	3010	3460
	Greece	500	500	500	500
	Montenegro	600	600	600	600
Sunday	France	1160	1160	1055	1055
	Switzerland	1910	1910	1660	1660
	Austria	145	145	100	100
	Slovenia	680	680	645	645
	Total northern border	3895	3895	3460	3460
	Greece	500	500	500	500
	Montenegro	600	600	600	600

The management of the electric network is primarily concerned with ensuring continuous balancing between the supply and demand, both domestically and internationally. This is achieved by controlling six essential characteristics, which are as follows:

- security: the ability of the system to withstand sudden disturbances while preserving its functional characteristics and ensuring uninterrupted power supply to users;
- stability: the ability of the system to return to a balanced state following perturbations in the electrical grid, such as electrical faults or power imbalances;
- resilience: the ability of the system to withstand stresses that exceed its operating limits and to return to normal operating conditions through temporary interventions;
- adequacy: the ability of the system to meet peak demand using available power resources, such as power supply, demand control, and limiting power exchange, with a margin of reserve;
- quality: The ability of the system to ensure continuity of service and quality of voltage and frequency;
- flexibility: the capacity of the system to respond to rapid changes without violating the constraints on the electrical grid.

The electricity requirement is characterized by a variable hourly profile which depends on different variables like the environmental climate, festivity and social-political events, this is why it is not possible to define a typical daily load profile. In order to demonstrate this concept, Figure 1.2 (a) compares two typical day during the month of April 2019: the blue line represents the weekday load profile 21 April 2019, while the orange one is the load profile during Easter day of 10 April 2019. These two figure highlight the load profile difference: the maximum gap between the blue line and orange line is about of 23.40 GW, starting from 46.66 GW for the blue line, going to 19.09 GW for the orange one.

The variability of the annual load profile is strictly related to three variables: economic growth, new kind of electrical load and energy efficiency. The Italy demand load was stable on a constant value of about 320 TWh in the last years, but the Covid-19 pandemic caused a drastic decrease in electricity consumption, in particular from March 2020, bringing the electrical demand to 302 TWh as is shown in Figure 1.2 (b).

It is important to note that the Covid-19 pandemic had a significant impact on the electricity demand profile, as many industries and businesses were shut down or limited their operations. This resulted in a decrease in the overall demand for electricity. However, as the pandemic subsides and economic activities resume, it is expected that the electricity demand will return to its pre-pandemic level and may even increase in the future due to the adoption of new technologies and the growth of electric vehicles. Therefore, it is essential for the power system to be able to adapt to the changing demand patterns and ensure the balance between supply and demand at all times.

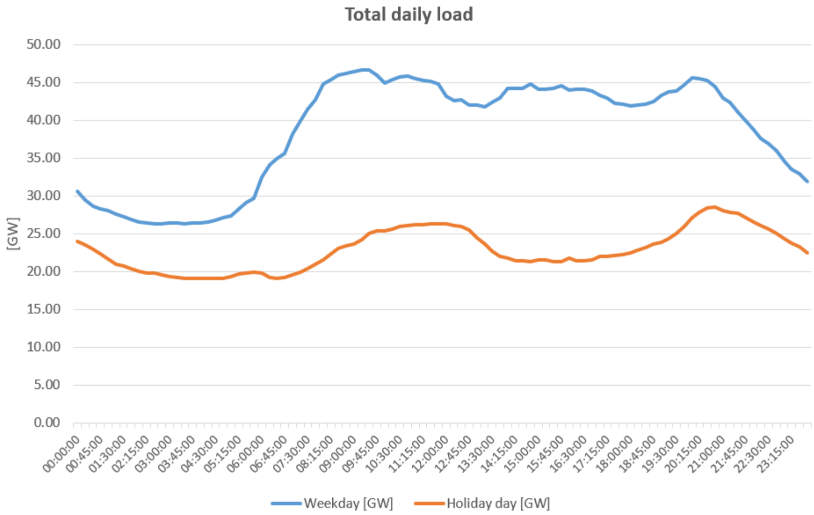
1.2 Italian electricity production and evolution of RESs

The composition of resources used in national electricity production has undergone significant changes in recent years, with a notable increase in the utilization of Renewable Energy Systems (RESs). In 2005, RESs contributed to 16 % of the total load demand, whereas by 2020, this figure had risen to 42 %. The trend of electricity production from traditional sources has decreased, being replaced by RESs, as shown in Figure 1.3.

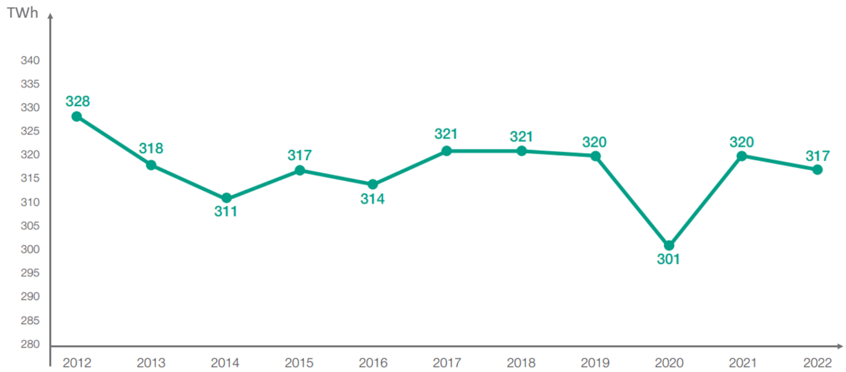
Between 2012 and 2013, there was a modernization and development phase of the Italian thermoelectric capacity, aimed at meeting the expected growth in energy demand and prices, resulting in an installed power of 77 GW. However, starting from 2013, the installation trend declined suddenly, leading to a significant reduction in the thermoelectric park in the following years, resulting in an available capacity of less than 60 GW. These changes are depicted in Figure 1.4.

The installed capacity of RESs in Italy is not uniformly distributed across the entire country. Specifically, in the year 2020, the total installed capacity of wind farms, which amounted to approximately 10 918 MW, was predominantly concentrated in the southern region, while the installed capacity of photovoltaic systems, which amounted to approximately 21 629 MW, was more evenly distributed throughout the country.

However, this transition to more sustainable energy sources presents certain challenges for managing the national electrical grid. This is because renewable energy power plants differ significantly from traditional power plants, as the former are connected to the national grid using static devices, such as inverters, while the



(a)



(b)

Figure 1.2. (a) Load comparison between a weekday 10/04/2019 and Easter day 21/04/2019. (b) Italy annual load demand profile from 2005 to 2022 [4].

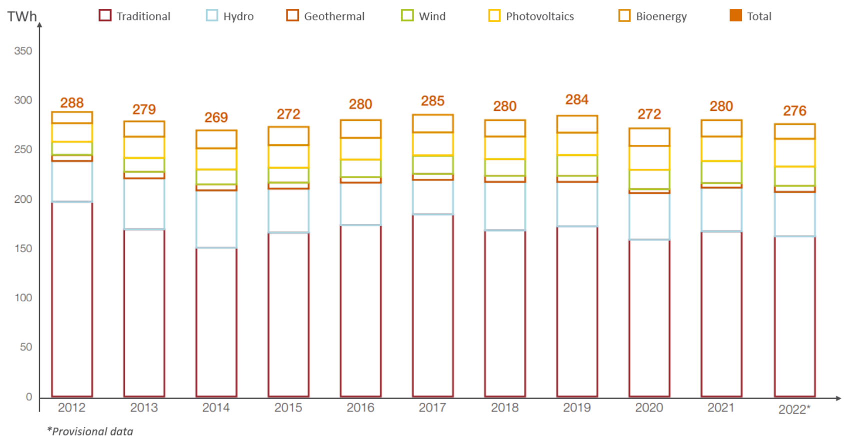
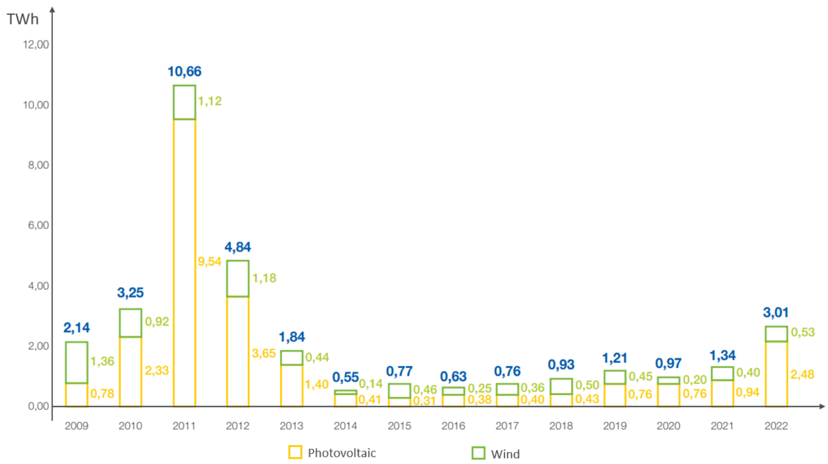
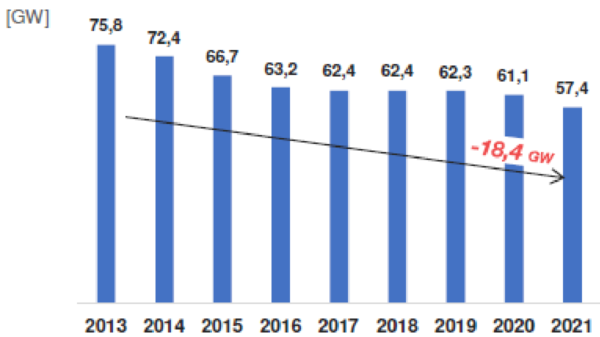


Figure 1.3. Evolution of net National net electricity production [4].



(a)



(b)

Figure 1.4. Behavior of the evolution of the Italian power plants capacity installed: (a) shows the evolution about the RESs [4]. (b) Shows the decline of traditional power plant capacity.

latter employ rotating components, such as synchronous machines.

The primary challenge associated with generating power from renewable energy sources RESs is that wind farms and photovoltaic power plants cannot be controlled programmatically. Consequently, the electricity generated by RESs does not align with the daily demand for energy. For example, photovoltaic generation is highest during sunny days and is zero during the night. Additionally, RESs generation can compromise the security and stability of the national electrical grid, thereby making it more difficult to respond to sudden failures on the grid. This issue arises because the RESs reduce the short circuit power at the nodes of the electrical grid, resulting in a reduction in system inertia, which is further exacerbated by the rapid decommissioning of conventional power plants.

These features of renewable energy sources RESs generation have a significant impact on the management of the electrical grid. These impacts include:

- reduced number of power plants capable of managing frequency and balancing active power supply and demand;
- reduced adequacy to meet peak power demand, particularly when RESs generation is low;
- growing phenomenon of over-generation during the central hours of the day;
- increased reserve requirements due to the greater presence of RESs and their uncertainty.

Terna aims to address these challenges through the installation of rotating machines (e.g., synchronous compensators) and static devices to manage voltage and power reactive variations. Terna plans to install the following static devices:

- Static Synchronous Compensator (STATCOM): power electronic devices that regulate input/absorbed reactive power and ensure system stability, even in the presence of strong RESs generation;
- shunt reactances: useful in areas with high voltage nodes when demand is low;
- stabilizing resistors: Useful for dynamic stabilization and damping of mains fluctuations.

As previously noted, the growth of RESs has not been uniformly distributed across the Italian territory, with wind farms predominantly located in the south of Italy (Puglia), often not matching local power demand. This aspect can create additional problems in managing the electrical system, including:

- increased network congestion due to the inconsistent location of RESs with places of consumption;
- new system management problems associated with the growing presence of generation plants on medium and low voltage networks.

All these problematic situations can compromise the "service quality", "security" and "efficiency" characteristics of the national electrical system grid.

1.2.1 Service quality

Service quality is an increasingly important aspect due to two significant factors: the growing use of electronic components for end-users' consumption and the increasing presence of electronic components for the automation of user systems. In particular, the service quality of an electrical grid system is considered good if it guarantees service continuity and power quality.

Regarding service continuity, this is related to a system's ability to ensure the transport of energy produced by generation plants to withdrawal plants that supply users. The primary transformation substations are connected to the sub-transmission grid, and therefore, the continuity of the distribution grid depends directly on the continuity of the high voltage grid.

While the benefits of distributed generation include voltage support, diversification of power sources, and improved reliability, power quality problems are also a growing concern. Faulty and bad wiring connections are responsible for approximately 70-80 % of all power quality issues. However, power frequency disturbances, electromagnetic interference, transient, harmonic, and low power factor can also threaten service quality associated with the types of sources and loads [7].

Indeed, the integration of photovoltaic and wind power stations, which are connected to the inverter, and the ramp characteristic of a non-linear load have caused harmonic problems in the electrical system. Additionally, harmonic problems can increase system losses up to 20 % [8]. In wind energy conversion systems, torque pulsation, low power factor, overheating, and increased stator winding losses can deteriorate overall efficiency [9].

The harmonic content in the power system can be evaluated using the Total Harmonic Distortion (THD). The THD is a measure of the effective value of the harmonic voltage (THDv) or current (THDi) in a distorted waveform. It represents the heating value of the harmonics relative to the fundamental and can be calculated using Equations (1.1) and (1.2):

$$THD_v = \frac{\sqrt{\sum_{h=2}^{h_{max}} V_{h,rms}^2}}{V_{1,rms}} = \frac{\sqrt{V_{2,rms}^2 + V_{3,rms}^2 + \cdots + V_{h,rms}^2}}{V_{1,rms}} \tag{1.1}$$

$$THD_i = \frac{\sqrt{\sum_{h=2}^{h_{max}} I_{h,rms}^2}}{I_{1,rms}} = \frac{\sqrt{I_{2,rms}^2 + I_{3,rms}^2 + \cdots + I_{h,rms}^2}}{I_{1,rms}} \tag{1.2}$$

where voltage and current harmonics vary from $h = 2$ to h_{max} and V_1 or I_1 refer to rms values of fundamental voltages or currents.

The harmonics can influence the power factor calculation too. In case of a sinusoidal voltage the power factor is defined as cosine of the angle between voltage and current and the ratio of the active power to the apparent power supplied by utility. In case of a non-linear load the True Power Factor (TPF) takes into account the contribution from all active power, including both fundamental and harmonic frequencies, like in equation (1.3) [10].

$$TPF = \frac{\frac{1}{T}\int_0^T v(t)i(t)dt}{\sqrt{\frac{1}{T}\int_0^T v^2(t)dt}\sqrt{\frac{1}{T}\int_0^T i^2(t)dt}} \tag{1.3}$$

In few words, the TPF is the ratio between the “average power” and the “apparent power”. The equation (1.3) may be written in terms of THDv and THDi as:

$$TPF = \frac{P_{1,avg}}{V_{1,rms} I_{1,rms}} \frac{1}{\sqrt{1 + (THDv/100)^2}} \frac{1}{\sqrt{1 + (THDi/100)^2}} \tag{1.4}$$

because of the THDv varies from 1.37 % to 10 % and the THDi varies from 10 % to 150 % [10], we can assuming negligible the THDv contribution and the equation (1.4) can be written in short form as:

$$TPF = \frac{P_{1,avg}}{V_{1,rms} I_{1,rms}} \frac{1}{\sqrt{1 + (THDi/100)^2}} \tag{1.5}$$

The power factor value can be fixed using different power electronics devices called Flexible AC Transmission Systems (FACTs), which can be used also in energy utilization, demand control, voltage stabilization, power quality enhancement, power flow control, voltage regulation and reactive compensation [11]. There are different types of FACTs devices such as Static VAR Compensator (SVC), Dynamic Flow Controller (DFC), Thyristor Controlled Series Compensator (TCSC), HVDC Back to Back (HVDC B2B), Unified Power Flow Controller (UPFC), Static Synchronous Series Compensator (SSSC), STATCOM, and Dynamic Power Flow Controller (DPFC). According to their connection, they are classified as shunt-connected controllers, series-connected and combined series and shunt-connected controllers. The FACTs components are based on:

- modulation of apparent admittance;
- injecting Alternate Current (AC) components in series or parallel with the electrical network nodes;
- supply localized reactive or capacitive current;
- modulating or switching the impedance at the interface bus by controlled switching.

There are various methodologies available to mitigate harmonics in the power system. The third harmonic and its multiples can be cancelled by delta-star transformer windings. The fifth and seventh harmonics can be reduced by winding pitch factors of generators. The significant harmonics are 11th and 13th, while the 17th, 19th, and higher order harmonics require attention. These higher-order harmonics can be avoided by load conditioning, which ensures that the electrical load is less sensitive to power disturbances. Installing a line conditioning system can also suppress or counteract power system disturbances [7].

Other methods to reduce the 11th and higher harmonics include using linear reactors, isolation transformers, k-factor transformers, tuned passive harmonic filters, IGBT-based fast switched harmonic filters, low pass harmonic filters, high pulse rectifiers, phase shifting transformers, and active harmonic filters [10].

One of the main indicators of power quality is the “number of voltage dips”, which represents the number of times the voltage value falls below 90 % of its rated value on at least one of the phases. This condition is usually caused by short circuit

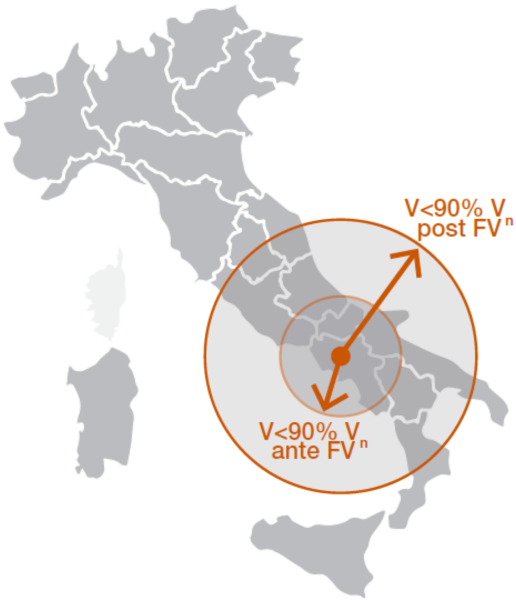


Figure 1.5. Extended area affected by the voltage drips, thanks to the strong RESs development [4].

events in the electrical grid, such as lightning strikes, and is extinguished within a few milliseconds thanks to automatic circuit breakers.

The extension of the area affected by the instantaneous voltage drop before the fault is eliminated is inversely proportional to the short circuit power S_{cc} of the network, according to the formula $\Delta V = \Delta Q / S_{cc}$. The short circuit power is maintained thanks to conventional power plants like thermal power plants. However, due to the evolution of RESs over the last two decades, the short circuit power has been reduced, resulting in a greater extension of the area affected by voltage dips, as shown in Figure 1.5.

1.2.2 Security

An electrical grid is considered to be “secure” if it can withstand sudden external disturbances without exceeding the system’s operating limits.

These disturbances can cause deviations in the electrical parameters from their nominal values. In order to prevent such deviations, the Italian Italian TSO employs a “Defense Plan” to restore the nominal frequency and voltage level to the electrical grid. The time it takes for the electrical system to recover from a disturbance is closely related to the level of inertia provided by conventional power plants.

However, power plants connected to the electrical grid through inverters (such as wind and photovoltaic power plants) do not provide the same level of inertia as conventional power plants, thereby reducing the electrical system’s overall inertia. This can cause significant challenges to maintaining the stability and security of the electrical grid.

An electrical grid is “secure” when it is able to resist changes in the operating status due to external sudden disturbances, without violating the operating limits system.

An external disturbance can cause to the electrical parameters a deviation from their nominal values. In order to avoid this phenomenon the Italian TSO enables the "Defence Plan", which can restore the nominal frequency and voltage level to the electrical system grid. The time it takes for the electrical system to re-establish the disturbance is closely linked to the inertia provided by conventional power plants.

The decrease in inertia in a system can cause:

- the frequency reduction is higher with a low inertia system than a high inertia system;
- in a low inertial system, the maximum frequency deviation is greater than a system with high inertia. Indeed, a minimum value is reached with a low inertial system.

1.2.3 Efficiency

An electrical system is considered efficient when it can operate the electrical grid in compliance with safety, adequacy, and quality requirements while minimizing overall costs for the user. The term "efficiency" is closely linked to both grid congestion and the increasing volumes traded on the service market.

This phenomenon is strongly connected to the non-uniform location of RESs. In fact, congestion problems have become more apparent in the central-southern regions of the country, where most RESs installations are concentrated, and where the grid experiences lower levels of interconnection and limited transport capacity.

Therefore, Terna has initiated the experimentation of a series of new services that will be progressively integrated into the electrical markets. These services aim to alleviate congestion problems and enhance grid flexibility, allowing for the better integration of RESs while maintaining reliable and secure grid operation, which are:

- UPR project: this project aims to enable the participation of relevant production units powered by RESs in the Ancillary Market;
- UVAM project: this project aims to enable the participation of non-relevant aggregates production, consumption, and accumulation units in the electrical markets;
- voltage regulation pilot project: this project aims to test voltage supply regulation services from both programmable and non-programmable resources.
- new projects focused on testing voltage regulation provided by RESs.
- new projects focused on testing the secondary regulation provided by RESs.

Chapter 2

The power flow algorithms in electricity markets

Power flow algorithms play a crucial role in power system operations, as they enable the management of the national electrical grid. One of the most important challenges in this context is addressing grid constraints, which must be adequately managed to ensure that the competitive electricity market functions fairly.

The aim of this chapter is to provide an overview of the Italian electricity market in Section 2.1. In Section 2.2, we will highlight the complexity of the problem at hand by describing the Unit Commitment (UC) and Optimum Power Flow (OPF) algorithms used in electricity markets. Finally, in Section 2.3, we will present a description of the OPF formulation.

2.1 The Italian Electricity Market

The Italian electricity market was established in 1999 with the enactment of Legislative Decree n. 79 [12], which aimed to transpose the EU Directive 96/92/EC [13] into national law. The market was later updated by the EU Directive 2003/54/EC [14] and Directive 2009/72/EC [15].

The electricity market in Italy is a virtual environment where wholesale electricity is negotiated between supply and demand. It is worth noting that participation in the power exchange is not mandatory in Italy, and operators have the option of negotiating contracts outside the power exchange, which is referred to as "optional exchange".

The Italian electricity market consists of the Spot Electricity Market (known as Mercato a Pronti dell'Energia (MPE) in Italian) and the Forward Electricity Market (known as Mercato a Termine dell'energia (MTE) in Italian). The Spot Electricity Market is further divided into three categories according to [16]:

- Day-Ahead Market: called in Italian Mercato del giorno Prima (MGP);
- Intra-Day Market: called in Italian Mercato Infragiornaliero (MI);
- Ancillary Services Market: called in Italian Mercato del Servizio di Dispacciamento (MSD).

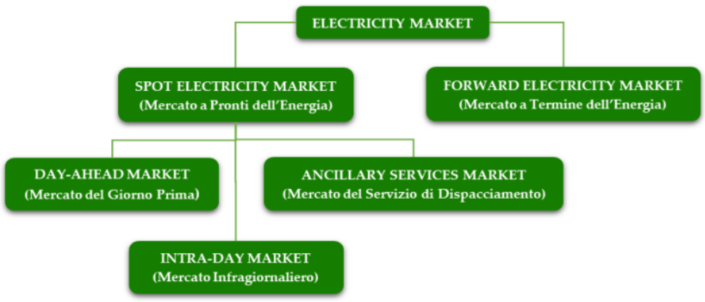


Figure 2.1. A description of the Italian Electricity Market Organization [16].

Figure 2.1 shows the structure of the Italian Electricity Market, providing the right match between the general definitions and the Italian name of each market session.

2.1.1 The Day-Ahead Market

The Italian Day-Ahead Market is the place in which the exchange of hourly supply offers and demand bids take place for the next day.

The Italian Nominated Electricity Market Operator (NEMO), managed by Gestore dei Mercati Energetici (GME), is responsible for managing and selecting offers and bids to maximize social welfare, taking into account transmission limits between bidding zones, which are notified by the Italian TSO, Terna.

In the Day-Ahead Market, hourly supply offers and demand bids for the next day are exchanged. The aggregate demand curve and the aggregate offer curve are sorted in descending and ascending price orders, respectively, as shown in Figure 2.2. The point where the two curves meet is called the balance point or the "marginal bid", denoted by q^*. The marginal bid represents the border where all bids to the left are accepted, and all bids to the right are rejected. The "market clearing price", denoted by ρ^*, corresponds to the price of the marginal bid. The area on the left between the aggregate demand curve and the aggregate offer curve is known as the Social Welfare (SW). The objective function of the Day-Ahead Market is to maximize the SW, which is calculated as shown in equation (2.1):

$$\max SW = \max \left(\sum_{j=1}^{n} \sum_{s=1}^{a} q_{s,j}(p_{s,j} - \rho^*) + \sum_{i=1}^{m} \sum_{s=1}^{b} q_{s,i}(\rho^* - p_{s,i}) \right) \tag{2.1}$$

where j is the number of consumption unit, i is the the number of production unit, s is the step accepted for that bid, a and b are the maximum steps accepted respectively for that demand curve and offer curve. So $q_{s,j}$ is the quantity demand accepted by the j-th consumption unit for the s-th step, $q_{s,i}$ is the quantity offer accepted by the i-th production unit for the s-th step, and the $p_{s,j}$ and $p_{s,i}$ are respectively the prices accepted for the production unit and consumption unit.

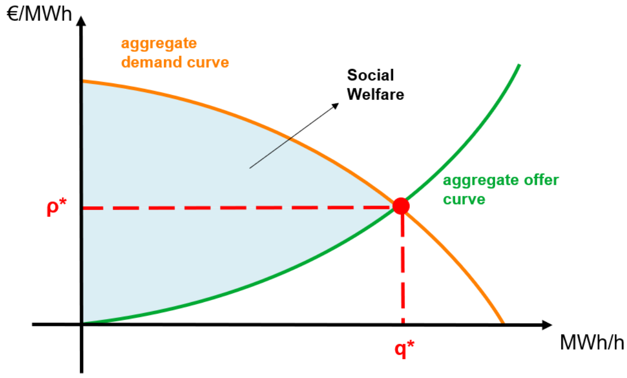


Figure 2.2. Example of one hourly session of MGP.

The equation (2.1) can be written shortly as the equation (2.2):

$$\max SW = \max \left(\sum_{j=1}^{n} \sum_{s=1}^{a} q_{s,j} p_{s,j} - \sum_{i=1}^{m} \sum_{s=1}^{b} q_{s,i} p_{s,i} \right) \tag{2.2}$$

Equations (2.1) and (2.2) are referred to the single hour of the day, therefore MGP performs 24 economic dispatch algorithms optimizing the SW.

Every seller receives a remuneration following the "market clearing prince" ρ^*, while every buyer receives a remuneration following a criterion based on the "Single National Price" (In Italian Prezzo Unico Nazionale (PUN)), this solution reserved for buyers is adopted only in Italy. The PUN is calculated during the MPG and its formulation consists on the average of zonal prices weighted for zonal consumption as the equation (2.3):

$$PUN = \frac{\sum_{z=1} \sum_{jz=1} \sum_{s=1} q_{s,jz} \rho_z^*}{\sum_{z=1} \sum_{jz=1} \sum_{s=1} q_{s,jz}} \tag{2.3}$$

where $q_{s,jz}$ is the energy accepted for j-th production unit in the z-th zone for that s-th step, and ρ_z^* is the market clearing price accepted for that geographical market area.

The elongated geographical configuration of Italy gives rise to certain unique characteristics in its electrical grid network, including bottleneck issues that make it challenging to optimize energy flows, particularly to the islands and between the northern and southern regions of Italy.

To address this issue, the electrical grid has been divided into different "market areas". Following the implementation of the European CACM Regulation [17], the Autorità di Regolazione per Energia Reti e Ambiente (ARERA) began a reviewing process at the national level to reconfigure the zones based on new criteria and procedures outlined in the regulation.

As shown in Figure 2.3, the evolution of the Italian market zones has progressed over time. The zonal configuration until 2018 comprised of six areas (North, Center North, Center South, South, Sicily, and Sardinia) and four poles of limited production. Starting from January 1st, 2019, a new zonal configuration was introduced which eliminated Brindisi, Foggia, and Priolo as poles of limited production. The current

Figure 2.3. Italian market zone's evolution.

zonal configuration, which came into effect on January 1st, 2021, comprises seven geographical areas (North, Center North, Center South, South, Calabria, Sicily, and Sardinia) with the elimination of the last pole of limited production in Rossano.

2.1.2 Intra-Day Market

The Intra-Day Market is a critical component of the electricity market, as it allows for adjustments to be made to individual market operators' results stemming from the MGP. This can help to balance contributions and/or withdrawals between the day-ahead market and real-time operations.

This overhaul involved alterations to both the quantity and nature of the market sessions and resulted in the integration of a new Intra-Day market, referred to as the Single Intra-Day Coupling (SIDC).

SIDC is now managed by the European Countries' NEMOs and TSOs. This means that now all market operators in every European nation (i.e. consumption units and production units) can modify their bids up until the hour of energy delivery.

The SIDC is a continuous trading market where the Continuous Trading Matching Algorithm (MCO) matches market bids, which opens at 15:00 of the day D-1 and closes each until the Intra Gate Closure of energy delivery at hour H-1. In this market, Italian operators have the option to submit portfolio bids to SIDC (one for each zone and for each operator, separately for production and consumption) and are required to nominate the corresponding positions for each unit within the H-1 hour.

Currently SIDC is divided into [18]:

- Cross Border Intra-Day (XBID): it is a continuous trading that facilitates the integration of energy markets across different countries or market zones by enabling continuous trading. This process allows market participants to submit bids and offers for buying and selling energy. If there is available interconnection capacity, these bids and offers can be coupled with those submitted by participants from other countries or market zones participating in the XBID;

- Complementary Regional Intra-Day Allocation (CRIDA): it is an addition to the Intra-Day continuous trading method. This augmentation enables the allocation of transmission capacity through regional implicit auctions. These auctions operate in conjunction with the Intra-Day continuous trading method.

SIDC works according to the “first-come-first-served” criterion and unlike the MGP, the TSOs communicate with the algorithm, which taking into account the Cross Zonal Capacity (CZC) and allocation constraints. Therefore, XBID is not a market that operates under optimal economic conditions, but rather associates offers by selecting those submitted first within the module called Shared Order Book.

Since it is not possible to provide a zonal price among the various Italian market zones through XBID, CRIDA has been introduced to replace the old MI auctions, defining the price of inter-zonal capacity involves determining the cost associated with transmitting electricity between different zones.

During the execution of CRIDA offers, continuous trading is interrupted three times in order to avoid overlaps between the offers of XBID and CRIDA.

Figure 2.4 provides a brief overview of how the SIDC operates.

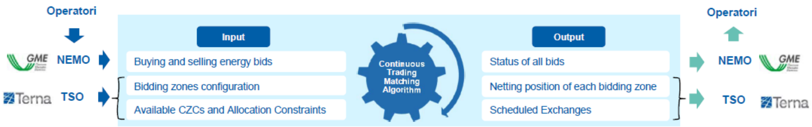


Figure 2.4. Summary of how the SIDC algorithm works.

2.1.3 Ancillary Market

The Italian Ancillary Service Market is a marketplace managed by Terna, where the trading of supply offers and demand bids for ancillary services takes place.

In this market, Terna selects resources to resolve congestion, procure frequency reserve, and ensure real-time balance of the power system. Generally, two types of payment methods are used for bids in the Ancillary Service Markets: the “clearing price market” (i.e., the MGP) and the “pay-as-bid” modality. The latter solution is utilized by the MSD.

The MSD is organized into two stages:

- a planning stage (Ex-Ante MSD in Italian), where Terna accepts offers and bids for relieving congestions and creating adequate reserve margins;
- a real-time Balancing Market (in Italian Mercato del Bilanciamento (MB)), where Terna accepts offers and bid in real-time for balancing the system and for relieving congestions.

Participation in the MSD is mandatory for generating units with an installed capacity greater than 10 MVA that are technically capable of effectively and predictably modulating their production and are qualified to supply ancillary services. These units are referred to as “Relevant Units”.

The primary objective of the MSD is to adjust generation and load schedules, which arise from energy markets, in order to resolve network congestion and other security issues, such as managing voltage and dynamic constraints, and to procure secondary and tertiary reserves.

The primary reserve is a response to the frequency variation of every production unit connected to the electrical grid, which is automatically delivered by the regulation speed of the generation group. If a frequency variation occurs, the TSO must intervene with 50 % of the primary reserve within 15 s and complete the action within 30 s. To do this, the TSO solves an Security Constrained Unit Commitment and Economic Dispatch (SCUCED) problem in the MSD by redispatching generation units (or switching them on/off) to resolve congestions and voltage constraints.

The secondary reserve, which corresponds to the EU automatic Frequency Restoration Reserve (aFRR), is activated within 180 s of a frequency variation. Its objective is to restore the primary reserve and compensate for the gap between the electrical requirement and production, restoring exchanges with other countries to their scheduled value. This service is an automatic function performed by a centralized controller located in the online control system of the TSO.

During the planning stage, the SCUCED algorithm adapts the schedules to ensure that there is enough secondary reserve capacity to cover the aFRR demand.

The tertiary reserve is divided into three categories:

- ready reserve: this product has a full activation time of 15 min, requiring a ramp rate of at least 50 MW/min. Its goal is to rebuild the secondary power reserve band and maintain the system balance in the event of rapid changes in demand;
- spinning reserve (which corresponds to the manual Frequency Restoration Reserve (mFRR)): this product has a full activation time of 15 min. Its goal is to replace the secondary power reserve band and the tertiary reserve ready;
- Replacement Reserve (RR): this product has a full activation time of 120 min. Its goal is to replace the spinning tertiary reserve when activated and to face potential deviations in demand and RESs infeed.

On the other side, the real-time Balancing Market intervenes only from the moment in which the control systems operating margins are compromise.

The Figure 2.5 summarizes the total Italian electricity market divided by session of each market typology described above.

However, the European TSOs proposed an implementation framework for a European platform in order to exchange the balancing energy from frequency restoration reserves, in accordance with the Commission Regulation (EU) 2017/2195 establishing a guideline on electricity balancing Guideline on Electricity Balancing (EBGL) [19].

Specifically, we are referring to Articles 19, 20, and 21 of the EBGL, which provide a framework for each type of balancing energy:

- Trans European Replacement Reserves Exchange (TERRE): this is the European implementation project for exchanging RR in accordance with Article 19 of the EBGL. The go-live date for TERRE was on January 13, 2021. The RR platform is based on the LIBRA solution, a system that pools available balancing energy bids and provides an optimized allocation of the bids to meet TSO imbalance needs. The TERRE project continuously works to enable stable operations and improve the optimization algorithm to better align with current market characteristics. The main difference introduced with TERRE

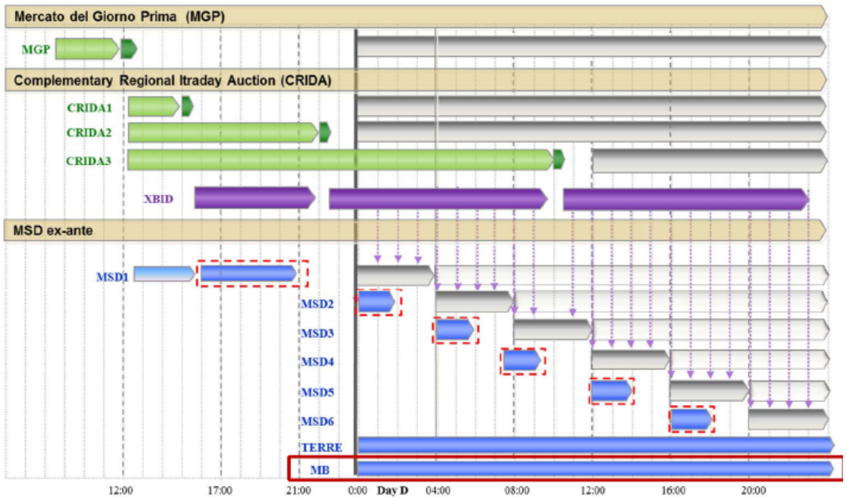


Figure 2.5. Italian electricity market divided by session of each market typology.

is that now bids are submitted by the TSOs with a planned schedule, and the accepted bids are paid based on their market clearing price;

- Platform for the International Coordination of Automated Frequency Restoration and Stable System Operation (PICASSO): this is the implementation project endorsed by all TSOs through the ENTSO-E Market Committee to establish the European platform for the exchange of balancing energy from frequency restoration reserves with automatic aFRR, in accordance with Article 21 of the EBGL. The go-live date for PICASSO is set for July 2023. The harmonization between the European TSOs is a direct result of the EBGL requirements, such as the platform to utilize merit order activation. Others will follow from the settlement proposals in accordance with Articles 30 and 52 of the EBGL. Otherwise, the full activation time can be divided into a preparation period (during which no energy is delivered) and a ramping period. The requirements for the preparation period vary across Europe as it depends on the mode of activation in use. Nevertheless, for aFRR, the preparation time remains very short as aFRR delivery is an automatic process;

- Manually Activated Reserves Initiative (MARI): this is the European implementation project for the creation of the mFRR platform, in accordance with Article 20 of the EBGL, and the go-live date is set for July 2024. This market serves the purpose of securing economically efficient purchase and timely activation of regulation energy while simultaneously ensuring the financial neutrality of the TSOs. The bids in MARI have two activation types: "scheduled only" (bids can be activated at the point of scheduled activation) and "direct" (bids can be activated at the point of scheduled activation and anytime during the 15-minute period after the point of scheduled activation). As in TERRE and PICASSO, bids are evaluated based on the clearing marginal price with a granularity of 1 MW and a Market Time Unit (MTU) of 15 min.

Figure 2.6 shows all European TSOs members and observer of TERRE, PICASSO

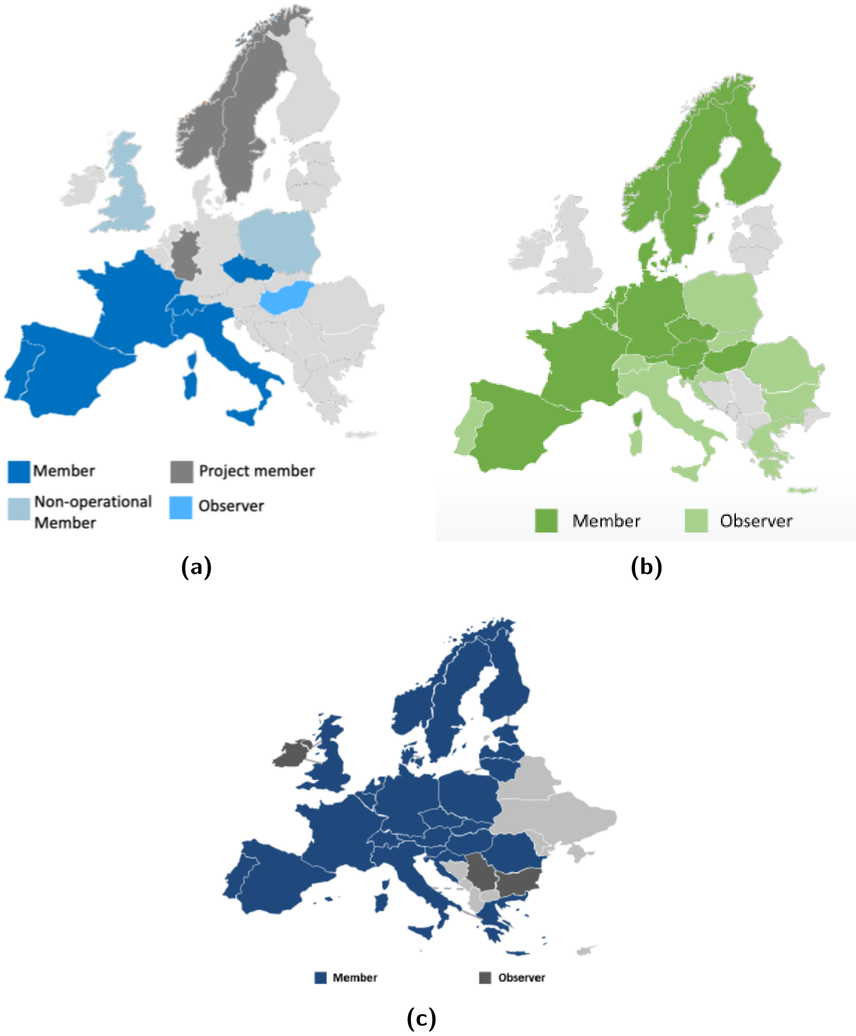


Figure 2.6. All the European TSOs members and observer of: (a) TERRE, (b) PICASSO, (c) MARI.

and MARI.

2.2 Unit Commitment and Optimum Power Flows in electricity market

As anticipated in Section 2.1.3, the objective of the UC activity is to determine the operational status (on/off) of production units during the different MTU of the simulated delivery time horizon. The UC problem is a Mixed Integer problem and is commonly referred to as the SCUCED problem, which is used by TSOs to meet the electricity demand at the lowest cost [20]. The SCUCED problem is challenging as it considers the upward and downward availability of production units, technical constraints (such as minimum uptime, minimum downtime, run-up rates, and run-down rates), and security constraints of the power system. In addition, security assessment must be integrated into the Unit Commitment and Economic Dispatch (UCED) problem using an OPF formulation, which would also consider the effect of contingency analysis. However, the exact formulation of the OPF problem is non-linear and complex.

Ackooij et al. [21] describes in its article that the UC solution methodologies can be classified into four categories: dynamic programming, Mixed Integer Linear Program (MILP) approaches, decomposition approaches and metaheuristics approaches.

In addition to the technical constraints of the production units, the algorithm shall cope with the security constraints of the power system, in order to deliver proper UCED choices. This would require the integration of a security assessment into the UCED problem, by means of an OPF formulation, which would also integrate the effect of contingency analysis. The OPF problem, in its exact formulation, is a non-linear problem.

Therefore, the SCUCED problem is a mixed integer non-linear and non-convex problem, which is particularly challenging to solve for large-scale power systems, even on a single scenario. This is due to the inclusion of the electrical network security constraints for market operation. Adding a stochastic modelization to the problem formulation would only increase its complexity and make it difficult to solve within a reasonable timeframe.

An extended description of the UC and Economic Dispatch (ED) problem can be found in [20] [22]. For the scopes of this handwritten, it can be simplified as in the following formula (2.4):

$$\min \sum_{i \in G} \left(\sum_{t \in T} \left(pr_{sell}^{i,t}\, q_{sell}^{i,t} + pr_{buy}^{i,t}\, q_{buy}^{i,t} \right) \right) \tag{2.4}$$

having as key constraint the energy balance in each point in time (2.5):

$$\sum_{i \in G} \left(u^{i,t} \left(q_{ini}^{i,t} + q_{sell}^{i,t} + q_{buy}^{i,t} \right) \right) = Demand^{i,t} \quad \forall t \in T \tag{2.5}$$

where G is the number of generation unit, T is the time horizon, $pr_{sell}^{i,t}$ is the sell price offered by generation unit i-th to increase its output from the initial schedule $q_{ini}^{i,t}$, $pr_{buy}^{i,t}$ is the buy price offered by generation unit i-th to decrease its output, $q_{sell}^{i,t}$ and $q_{buy}^{i,t}$ are the accepted incremental/decremental quantity and $u^{i,t} \in [0, 1]$ is the commitment variable of the production unit.

Additional constraints are typically added to this basic formulation, such as:

- power flow equation;
- transmission flow constraints;
- system spinning and operating reserve requirements;
- ramp rate limitations;
- startup and shutdown characteristics of units;

- any additional security constraints provided by the System Operators as resulting from other studies (e.g., dynamic assessments).

At present, the solution to the SCUCED problem is commonly carried out by system operators worldwide through a two-step iterative approach [23]:

- market clearing algorithm: which treats the SCUCED as a Mixed Integer problem without incorporating power flow equations, but introduces linear constraints to reflect security constraints such as maximum loading of critical network elements and contingencies;

- security assessment module: in which solves the power flow problem independently for each MTU, considering both the base case scenario (N state) and all relevant contingencies (N-1 assessment). This module identifies potential binding critical network elements and contingencies and computes the associated power transfer distribution factors. These factors are used to formulate linear constraints into the market clearing algorithm to determine a UC and ED solution capable of managing such congestions. Occasionally, a Direct Current (DC) formulation of the power flow equations is employed, and an AC final check is conducted.

Nevertheless, in this approach, handling voltage and reactive power constraints poses a challenge and they are often simplified in the modelling process. Low voltage issues are typically reflected by limiting the transmission capacity on a set of lines, while high voltage issues are modelled by introducing UC constraints, such as a minimum number of units from a given set of power plants that must be online. However, this approach may be inefficient since the complex interaction between active and reactive power, as well as the ability to resolve voltage issues through other remedial actions (such as managing shunt reactors, synchronous compensators, and High Voltage Direct Current (HVDC) links), is only partially represented.

In addition to the aforementioned complexities, when a power system has high penetration of intermittent RESs and the electricity demand is highly dependent on weather conditions, it is crucial to account for the uncertainties in the expected operational scenario, including hourly demand and RESs generation profiles and their geographical distribution. Stochastic approaches have been applied to the UC problem to handle these sources of uncertainties. The problem is solved by considering multiple operating scenarios, each characterized by a probability of occurrence [24] [25] [26]. In these approaches, the following variables are usually treated as stochastic: solar generation, wind generation, demand, and thermal capacity of overhead transmission lines when dynamic line rating strategies are implemented.

It is important to note that implementing a stochastic SCUCED approach would require system operators to develop predictive algorithms that can provide not only the expected value of each variable but also their distribution function. Ideally, these algorithms should generate scenarios with assigned probabilities, taking into account the autocorrelation and cross-correlation between variables and across space.

2.3 Optimum Power Flows formulation

Several TSOs adopt an OPF to ensure the security of the power system in real-time while minimizing costs for redispatching.

The OPF is an optimization problem aimed at minimizing an objective function that includes the (re)dispatching costs, considering the following variables: the active power generation P_g, the reactive power generation Q_g, the nominal line to line voltage V and the voltage phase angle ϑ.

The problem can be summarized with the formula (2.6) [27]:

$$\begin{aligned} \min_{P_g, Q_g, V, \vartheta} \quad & f(P_g, Q_g, V, \vartheta) \\ s.t. \quad & g(x) \leq 0 \\ & h(x) = 0 \end{aligned} \tag{2.6}$$

where the $h(x)$ and $g(x)$ are constraints respectively of equality and inequality. The equality constraints concern the balance of electrical powers like the (2.7) and (2.8):

$$P_i = \sum_{j=1}^{n} 3\, E_i\, E_j\, Y_{ij} \cos(\vartheta_i - \vartheta_j - \gamma_{ij}) \tag{2.7}$$

$$Q_i = \sum_{j=1}^{n} 3\, E_i\, E_j\, Y_{ij} \sin(\vartheta_i - \vartheta_j - \gamma_{ij}) \tag{2.8}$$

while the inequality constraints are the equation from (2.9) to (2.14):

$$P_{ij}^2 + Q_{ij}^2 \leq S_{max,ij}^2 \tag{2.9}$$

$$I_{i,Re}^2 + I_{i,Im}^2 \leq I_{max}^2 \tag{2.10}$$

$$P_{g,min} \leq P_g \leq P_{g,max} \tag{2.11}$$

$$Q_{g,min} \leq Q_g \leq Q_{g,max} \tag{2.12}$$

$$V_{i,min} \leq V_i \leq V_{i,max} \tag{2.13}$$

$$\vartheta_{ij,min} \leq \vartheta_{ij} \leq \vartheta_{ij,max} \tag{2.14}$$

The (2.9) and (2.10) are the thermal limit of the i-th in terms of power and thermal capacity, the (2.11) and (2.12) are the maximum and minimum limit of the active and reactive power generated, finally the inequalities (2.13) and (2.14) represents the upper and lower limits allowed for the voltage V at the i-th node and for the angle phase ϑ between the i-th and j-th node of the electrical grid.

Since the constraints described from (2.9) to (2.14) are convex functions the computational burden is not compromised at all, the non-convexity of the OPF problem comes from the power flow equations (2.7) and (2.8). Another important thing is that the standard OPF formulation does not consider the UC problem, so the OPF does not resolve automatically the discrete variables. In fact, the UC problem introduces in the OPF a non-linearity caused by its discrete variables, which increase the computational burden of the algorithm.

Chapter 3

The state of art about the Optimum Power Flow algorithms

Because the OPF problem was first formulated in the 1960s, a multitude of solution algorithms have been proposed increasing more and more the speed of solution and minimizing the risk of non-convergence of the algorithm. This feature enables practical industrial implementation in power system management contexts, in fact Terna adopts an OPF algorithm for the resolution of the real-time balancing market.

Thanks recent progress in implementing new OPF models and the way in which power flow equations are processed, we can divide the existing OPF algorithms into the following categories:

- OPF methods with the strict AC network model: in these methods, the original formulation of the (2.7) and (2.8) power flow equations of the AC network model are considered when optimizing. The relevant OPF model is also known as the Alternate Current Optimal Power Flow (ACOPF) model. Non-linear optimization techniques are used to address the OPF problem, due to the non-convexity and the non-linearity of ACOPF [28] [29];.

- OPF methods with linearized network models: the non-linear equations are replaced with a linearized and approximate one, this method is called “DC method”. In this way, the computational load is reduced, the computational efficiency can be greatly improved and convergence can be ensured, even if the precision of the modeling is sacrificed. This formulation is widely used in the power sector and in market operation thanks to its ability to cope with strict market timings [30] [31];

- OPF methods based on convex relaxation: this approach relaxes the power flow equations (2.7) and (2.8) into inequalities that define a convex region. These techniques are closer to the exact outcome of the problem than the DC form, but require increased computing effort. The convex relaxation method is a compromise between the OPF AC model and the DC one [32] [33].

3.1 The OPF methods

The three OPF methodologies described in the above list have been researched and developed for many years to enhance their implementation. Since we can find in literature an huge amount of papers which describe their application from balancing market to the study that ensure the electrical network security and reliability, also considering RESs.

Each methodology has got benefits and drawbacks, differentiating the study environment and the use of each algorithm.

3.1.1 OPF Methods with ACOPF

The non-linearity and non-convexity of the ACOPF problem make it challenging to solve using traditional optimization methods. The power flow equations (2.7) and (2.8) are nonlinear equations that relate the active and reactive power flow to the voltage angles and magnitudes in the power network. These equations are highly coupled, which makes it difficult to obtain a closed-form solution for the optimization problem.

Several Nonlinear Programming (NLP) algorithms can be applied to solve the ACOPF problem, including the Newton method, Linear Programming (LP) methods, and metaheuristics methods. The LP approach takes advantage of the weak coupling between active and reactive power and the quasilinear relationship between active power P and voltage angles ϑ. For some LP methods, the OPF optimization problem is decoupled into active and reactive sub-problems, which simplifies the optimization problem.

Another approach to solving the ACOPF problem is to use approximations that linearize the power flow equations and voltage and current constraints. One such method is to use the Taylor series approximation stopped at the first order, which results in a linearized version of the power flow equations and quadratic constraints. This method can be applied to solve the ACOPF problem efficiently and accurately, especially for small to medium-sized power systems.

The approaches described above differ from the DC ones because they maintain the reactive power equation (2.8), which instead is not considered in the DC approach.

Currently, it is very difficult for System Operators to apply these algorithms in clearing markets, day-ahead markets or real-time scheduling, as long as their computational convergence cannot be guaranteed, although it has the advantage of introducing the voltage constraints into its formulation through exact modelling.

3.1.2 OPF Methods with Linearized Network Models (DC Method)

Linearized network models for OPF methods have become popular among system operators due to their desirable computational performance. These methods intend to linearize the power flow equations (2.7) and (2.8) to facilitate the linear formulation of the OPF model following a DC approach.

The advantage of the linear optimization model is its transparency, and the influencing factors in the OPF model are linearly coupled. However, some limitations must be considered:

- the active power equation (2.7) is considered, but the reactive power equation (2.8) is not;
- the network elements considered are only represented by their own longitudinal reactance, neglecting other parameters that affect the power flow;
- the nodal voltage module is considered constant, and the $\Delta\vartheta$ between the i-th and j-th node are "close", i.e. $\vartheta_j - \vartheta_i \approx 0$. This assumption may not hold for all network conditions and can lead to inaccuracies in the solution.

The matrix of nodal admittances $[Y]$ becomes a matrix of susceptances, denoted by $[B]$. In the linearized DC model, the elements of $[B]$ are linked only to the longitudinal reactances of the branches. The approximation of the sine function is used to linearize the power flow equations (2.7) and (2.8) and obtain the linear relation between the active power injection and the voltage phase angle difference between two buses.

$$P_i = \sum_{j=1}^{n} 3E_iE_jY_{ij}\cos(\vartheta_i - \vartheta_j - \gamma_{ij}) = \sum_{j=1}^{n} B_{ij}\sin(\vartheta_i - \vartheta_j) \approx \sum_{j=1}^{n} B_{ij}(\vartheta_i - \vartheta_j) \tag{3.1}$$

The (3.1) can be written in the (3.2) form:

$$[P] = [B][\Delta\vartheta] \implies [\Delta\vartheta] = [B]^{-1}[P] \tag{3.2}$$

Concluding, the DC approximation methods are widely used by system operators to solve the OPF problems in electrical markets, thanks to their low computational burden and the secure convergence. In fact, the Direct Current Optimal Power Flow (DCOPF) is a convex problem and for this reason, it is easily solved. However, the DCOPF lacks solution accuracy because reactive power is not considered, so that voltages are set to their nominal value. On the other hand, the drawback of DCOPF is that the voltage constraints are not considered in the algorithm, which are a prerogative for several System Operators in order to guarantee the electrical network grid security.

3.1.3 OPF Methods Based on Convex Relaxation

Due to the non-linear nature of power flow equations, they describe a non-convex region, which poses a challenge in solving the OPF problem. The task of convex relaxation is to modify equations (2.7) and (2.8) to define a convex region.

One example of an OPF model based on convex relaxation is presented by Z. Yang et al. [27], while Steven H. Low [34] provides a comprehensive formulation of the convex relaxation.

Convex relaxation methods involve selecting a positive semi-definite matrix to optimize a linear function, subject to linear constraints. In other words, the well-known linear programming problem is extended by replacing the vector of variables with a symmetric matrix, and the non-negative constraints with a positive semi-definite constraint. Therefore, in convex relaxation problems, we study two different formulations of the problem: the "primal" and the "dual".

Since the Unit Commitment Optimal Power Flow is a non-convex Mixed Integer Non-Linear Program (MINLP), the use of relaxation techniques is a common approach to solve non-convex optimization problems. Among the different relaxation techniques available, the most popular ones are Semidefinite Programming Relaxation (SDP), Second-Order Cone Programming Relaxation (SOCP), and Quadratic Programming Relaxation (QP).

When the relaxation technique is applied to the dual problem and the optimal solution of the relaxed model is also feasible to the original primal problem, then the relaxed model is said to achieve the global optimum of the original problem. The Interior Point Method (IPM) is one of the best algorithms to solve the relaxed model of the OPF problem in NLP form.

However, the use of relaxation techniques may introduce a duality gap, which leads to a suboptimal solution. To overcome this issue, the Lagrangian Relaxation (LR) method has been introduced to find a feasible solution for the original problem.

In the literature, different authors have used different relaxation techniques to solve the Unit Commitment Optimal Power Flow problem. For example, N. Li et al. [35] and S. Huang et al. [36] have used SOCP relaxation in their studies. In this approach, the quadratic equality constraint (3.3) is transformed into an inequality constraint (3.4), which simplifies the problem and makes it easier to solve.

$$|I_{i,j}|^2 = \frac{P_{i,j}^2 + Q_{i,j}^2}{V_i} \tag{3.3}$$

$$|I_{i,j}|^2 \geq \frac{P_{i,j}^2 + Q_{i,j}^2}{V_i} \tag{3.4}$$

3.2 Review on stochastics OPF Methods

This section describes some key study cases found in literature, illustrating the application of the SCUCED resolution techniques. These studies can be useful to Terna to find suggestions on how to modify the features of the MSD algorithm in order to take into account the voltage constraints and improve the reliability of the electrical grid.

The strong penetration of RESs is making it difficult for Terna to balance the electrical supply and demand with the Ancillary Markets, and is threatening the reliability of the Italian electrical grid. In addition, the variability of operating conditions is increasing due to the presence of RESs, which is also affecting the electrical load forecasting. To address these issues, Terna is reformulating a new MSD algorithm that explicitly considers the voltage constraints and uses stochastic approaches to handle forecast uncertainty.

The features of the new MSD algorithm are:

- integrated evaluation and resolution of voltage constraints;
- explicit treatment of forecast uncertainty using stochastic approaches;
- transposition of the European directives about the implementation of a 15 min MTU (which therefore extends the number of time intervals considered by the

algorithm from 24 to 96). Currently, Market Time Unit has got a maximum of 24 MTU.

So the goal is the implementation of an algorithm that solves a problem of Security Constrained Unit Commitment (SCUC) with the following requirements:

- formulation of the OPF problem in AC (therefore with explicit treatment of the reactive problem and of the voltage constraints);
- implementation of N and N-1 security criteria, including the logic of the defense plan;
- optimization of Phase Shifter Transformer and the HVDC links;
- explicit management of stochastic variables, through integrated resolution of multiple load scenarios and RESs generation;
- high convergence reliability and robustness;
- resolution times compatible with market processes (i.e. resolution of the daily problem on a network with about 1500 nodes/1500 branches/200 dispatchable generators in less than 1 hour).

This study aims to fill the gap in the literature by identifying the best available solution that meets fixed goals for the UC and ED problems in the context of OPF. Currently, there is no algorithm in the literature that takes into account all the features of the new MSD algorithm proposed by Terna, and this study attempts to collect all the information from partial solutions found in the existing literature.

The literature review was conducted by starting from the state of the art of OPF-based UC and ED problems, including relevant existing reviews. The study then focused on the stochastic examination of the OPF algorithm, as the optimal scheduling of power generation units must consider the possibility of prediction errors and equipment failure. In fact, the problem of stochastic unit commitment is related to the scheduling of production units during periods of uncertainty.

By collecting and analyzing the existing literature on UC, ED, and stochastic unit commitment, this study aims to identify the best available solution for the new MSD algorithm proposed by Terna. This solution will take into account the voltage constraints, handle forecast uncertainty using stochastic approaches, and consider the transposition of the European directives regarding the MTU.

3.2.1 Review on OPF Methods for UC and ED

The study of OPF methods for UC and ED problems requires an understanding of the problem structures. Z. Yang et al. [27] provide a comprehensive analysis of the OPF problem, including the reasons for its difficulty and how the non-linear power flow equations cause non-convexity. The authors classify OPF algorithms into three categories: strict AC network models, convex relaxation-based methods, and linearized network models.

The authors compare these three categories in terms of computational efficiency, convergence, solution quality, and industry preferences. The AC formulation is the

Table 3.1. Summary of the three OPF resolution methods.

Properties	**OPF methods with strict AC**	**OPF methods based on convex relaxation**	**OPF methods with linearized network models**
Computational burden	Nondeterministic Polynomial-time (NP) hard problem	Terminate in a polynomial time; complexity is easier to harder: SOCP<QP<SDP	Terminate in a polynomial time; easy to perform
Convergence	Not guaranteed	Guaranteed	Guaranteed
Solution interpretation	Obtained solution strictly subject to power flow equations and operational limits; obtained solution may be a local optimum	If the "dual" problem is exact, so the "primal" problem converges	Solutions are strictly subject to the linearized active power; solution close to the DC equation
Area of application	Currently used for the optimization of reactive power	No evidence of industrial applications	Currently used in the clearing engine of power markets and power system planning

hardest to solve, while the DC formulation is easier. The computational burden of the convex relaxation formulation can be ranked as low for SOCP, moderate for QP, and hard for SDP, although all three can terminate within a polynomial time. Convergence is only guaranteed for the convex relaxation and DCOPF formulations.

In terms of industry preference, system operators require computational accuracy, efficiency, and robustness, and prefer LP optimization problems and OPF methods based on linearized network models for market clearing, power system planning, and other applications. ACOPF methods are used for optimizing reactive power and voltage magnitude, such as in tertiary voltage control.

The Table 3.1 illustrates the comparison of the three OPF resolution method mentioned before.

I. Abdou et al. [37] give a literature review of UC problem based on articles and works published since 1959 until now, including classical methods such as the Branch-and-Bound algorithm, Lagrangian Relaxation, dynamic programming, as well as more recent approaches such as meta-heuristics, genetic algorithms, artificial intelligence techniques and mixed integer programming combinatorial optimization problem with constraints, or simply named MINLP. The authors emphasize that the choice of the solution method depends on the problem size, complexity, and solution quality requirements, and that there is no universal best method for solving all instances of the problem.

In recent years, the integration of renewable energy sources in power systems has become a major concern in the UC problem. This is due to the intermittent and uncertain nature of renewable energy sources, which can lead to an increase in operating costs and a decrease in system reliability if not properly accounted for in the UC model. To address these issues, various approaches have been proposed in the literature, including stochastic programming, robust optimization, scenario-based optimization, and chance-constrained programming. These approaches aim to incorporate the uncertainty of renewable energy sources into the UC model and to ensure that the system is able to meet the demand under all possible scenarios.

Most researches in this field have recognized that critical decisions associated with the operation of the power system can be effectively represented by integer (binary in general) variables, so classical linear programming approaches are not able to clearly model and solve such complicated problems. For this purpose, is preferable to use a MILP formulation, where the commitment decisions indicating the on/off status of the generating units in various operating phases (offline, start-up, dispatch, and shutdown) are modelled using binary variables, while the power output, reserve contribution, and flow decisions are represented using continuous variables.

Overall, the article by I. Abdou et al. [37] provides a comprehensive review of the UC problem, its mathematical formulation, solution methods, and approaches for addressing renewable energy effects and uncertainties.

The MILP deterministic of the SCUCED problem may be formulated in a manner that minimizes operational costs:

$$\min OC = \min \sum_{i \in G} \left(\sum_{t \in T} (FC_{i,t}(P_{i,t}) u_{i,t} + NL_i + ST_{i,t} + SD_{i,t}) \right) \tag{3.5}$$

$$FC_{i,t}(P_{i,t}) = a_i P_{i,t}^2 + b P_{i,t} + c_i \tag{3.6}$$

where OC the operating cost, G is the number of generation units, T is the time horizon, $u_{i,t}$ is the binary variable modelling UC decision of unit i-th at hour t-th, $FC_{i,t}$ is the fuel cost modelled as a quadratic function of the power output, a_i, b_i and c_i are the cost coefficients, NL_i is the no-load cost of unit i-th and $ST_{i,t}$ and $SD_{i,t}$ are respectively the startup and shutdown costs of unit i-th at hour t-th.

Due to the high level of complexity involved in solving the SCUCED problem, various solution techniques have been employed in the past. Since the 1970s, it has been recognized that many difficult problems can be simplified by adding a relatively small set of side constraints. This is the basic principle behind the LR and Bender Decomposition (BD) methods.

The LR method involves solving a relaxed problem where the original problem is replaced with the dual one. By dualizing the side constraints, a Lagrangian problem is produced which is easier to solve, and whose optimal value serves as a lower bound for minimization problems on the optimal value of the original problem. The Lagrangian problem can be used as a replacement for a linear programming relaxation in a branch and bound algorithm. The Lagrangian approach offers several advantages over linear programming, as demonstrated in [38].

The BD approach breaks down the original Security-Constrained Optimal Power Flow (SCOPF) problem into a master problem and several slave sub-problems which interact iteratively. It also allows computations to be distributed among several processors, which can considerably speed up the overall process. However, BD requires the feasibility region to be convex, which cannot always be guaranteed in the case of ACOPF. Therefore, BD must be used with caution, as stated in [39].

Since the UC problem is formulated as a MILP problem, and the ACOPF is an NP-hard non-convex non-linear problem, combining UC and ACOPF poses a significant challenge in terms of finding an effective solution.

The article by A. Castillo et al. [40] proposes a novel approach for generating financially viable schedules for UC that are also physically feasible on AC power systems. They investigate the co-optimization of real and reactive power scheduling and dispatch, which is referred to as the UC problem subject to AC optimal power flow (UC+ACOPF) constraints.

The Outer Approximation (OA) algorithm is another technique used for solving MINLP problems. It is an exact algorithm that assumes convexity, differentiability, and constraint qualifications. Generalized Bender Decomposition (GBD) is a particular case of OA, where the lower bounds are typically weaker than those predicted by OA.

In their article, A. Castillo et al. [40] propose applying the GBD method through successive iterations with Taylor series approximation, which divides the MINLP problem into a master MILP problem and several NLP sub-problems. These sub-problems are solved using a Successive Linear Programming approach. GBD is applied to both classic UC and SCUC. The main difference between OA and GBD is that the lower bounds of the latter are generally weaker, meaning that the lower bound predicted by the relaxed master problem of OA is likely greater than or equal to that predicted by the master problem of GBD.

The results of this proposed strategy show good performance, considering that the problem has been solved with a 2.2 GHz Intel Core i7 and 16 GB RAM calculator. For the scope of this paper, it is very interesting to note that the UC based on the ACOPF is 5–10 times slower than a DCOPF. Moreover, the tests are performed on a power system 10 times smaller than the Italian one.

In their article [41], J. Liu et al. introduced a new algorithm for solving the network-constrained unit commitment problem that includes a non-linear AC model of the transmission network. The algorithm is based on the multi-tree global optimization methodology, which alternates between solving a Mixed Integer lower-bounding problem and a non-linear upper-bounding problem.

The lower-bounding problem in their approach includes a relaxation and outer-approximation of the full set of ACOPF constraints, which sets it apart from previous approaches such as GBD methods applied to the UC-AC problem.

Their algorithm uses a "nested" multi-tree approach, where both the outer and inner algorithms are based on a non-convex OA approach that solves a series of lower-bounding master problems and upper-bounding sub-problems. The master problem is a relaxation of the SCUC AC problem, where the AC power flow constraints are relaxed using a second-order relaxation method. The master problem provides a lower bound on the SCUC and a candidate solution for the generator commitment variables, while the NLP sub-problems provide an upper bound and a candidate solution for the SCUC AC problem. If the difference between the upper and lower bounds is sufficiently small, then a solution has been found.

The results of this study show a performance comparison with the approach announced in [41], for the global case is used a 64 bit server with 24 CPUs (Intel(R) Xeon(R) CPU E5-2697 v2 @ 2.70 GHz) and 256 GB RAM. It is evident how increasing the size of the power system the optimality gap of the local approach increase too, while the optimality gap of the global approach remains substantially contained, nevertheless with calculation times significantly longer and completely incompatible for market operation. So, the time of solution is from 3.6 s for the 6-bus system to 115.23 s for IEEE-118 system, however even here the tests are performed on a power system 10 times smaller than the Italian one.

So it could be of interest to observe the performance of these algorithms when applied to a real case study, such as the Italian context. If this proves to be too challenging, an alternative approach could be to study the algorithm's performance when applied to a subset of the Italian network. This approach can prove useful in comprehending the real-world behaviour of SCUCED algorithms, as the literature contains examples of case studies involving 'laboratory' networks.

3.2.2 The Stochastic Algorithms Review

Nowadays, the increasing capacity for renewable energy generation, such as wind and solar power, has significantly amplified the levels of variability and uncertainty in the power system. As a result, the ideal model for UC has become a large-scale, non-convex, and uncertain program. Despite its intermittent nature, the integration of RESs into the power system is mainly justified by its economic and environmental benefits for the system.

Terna, aims to employ a stochastic approach in its new MSD algorithm to solve the UC and ED problem effectively. This stochastic approach can consider aleatory variables such as wind power and solar power, taking into account several operating scenarios characterized by their probability of occurrence. Thus, an optimal solution that minimizes the expected cost of the operating system can be determined.

When a power system is heavily penetrated by intermittent RESs, and electricity demand is strongly dependent on weather conditions, it is crucial to consider uncertainties in the expected operational scenario, such as hourly demand and RESs generation profile and geographical distribution. Stochastic approaches have been applied to the UC problem to cope with these sources of uncertainties, whereby the problem is solved by considering several operating scenarios, each characterized by its probability of occurrence [24] [25] [26].

The stochastic variables are important in the new MSD algorithm, because the contribution of the RESs is preponderant for the National electrical grid reliability. An example of stochastic variables can be:

- the photovoltaic plants;
- the wind farms;
- the thermal capacity of the air line.

The thermal capacity is a stochastic variable since it can vary depending on solar irradiation and wind power. Therefore, it is essential to find an appropriate mathematical model that can predict such variables and incorporate them into the "Stochastic Optimal Power Flow".

L. Wu and M. Shahidehpour [42] discuss three solution techniques proposed for managing uncertainties in SCUC, which are reviewed and summarized by I. Abdou and M. Tkiouat [37]. These techniques are:

- Stochastic Programming (SP): a renowned optimization technique to solve SCUC problem with uncertainties. In the SP approach, power system uncertainties are represented by a set of scenarios for the possible realization of different uncertainties. SP technique is based on a scenario tree in which uncertainty is supposed to be known in each node as long as uncertainty may be discretized on the tree, essentially the quantity for solving a deterministic large-scale UC problem. Every scenario is attributed a certain probability for its realization;

- Robust Oprimization (RO): is an alternative technique for dealing with uncertainties in the SCUC problem. RO uses the notion of uncertainty set in order to be less demanding on the representation of uncertainty, which assembles the adverse events against which we wish to protect ourselves. This uncertainty set considers a limited level of information on uncertain quantities, namely the mean value and some estimate of the variance or a range of possible variations around the mean;

- Chance Constrained Optimization (CCO): is the third approach to handle the uncertainties in the hourly SCUC problem, in which temporal constraints can be violated with a predefined level of probability. CCO appears as a good alternative to select the trade-off between cost and robustness of the electrical network.

M. Håberg [43] proposes a classification of the latest stochastic programming literature based on the formulation and decomposition methods used. The models in literature are categorized into two categories: "two-stage" and "multi-stage" models. The stochastic unit commitment problem takes uncertainty into account through scenarios in the "two-stage" model. The "multi-stage" model differs from the "two-stage" model in that information on uncertain parameters is not given all at once but is obtained at intervals throughout the planning horizon.

Furthermore, [43] distinguishes between "scenario decomposition," "unit decomposition," "Benders-like decomposition," "dual decomposition," and approaches using "no decomposition":

- scenario decomposition: in this approach, the stochastic problem decomposes into separate deterministic unit commitment problems for each scenario;

- unit decomposition: this approach decomposes the problem into single-generator stochastic programs, which can be solved separately, e.g. using dynamic programming;

- Lagrangian Relaxation: this technique can be applied to the demand constraint to decompose the problem into a single-generator problem;

- Benders-like decomposition: in this approach, cuts are added to the master problem (first-stage) based on the evaluation of the subproblem (second-stage);
- dual decomposition: this approach uses LR of the non-anticipativity constraints to obtain a Lagrangian dual function that is separable for each scenario. Solving the Lagrangian dual problem provides a lower bound to the solution of the primal problem.

P. Nikolaidis et al. [44] have presented a new approach to address the robust UC problem, which considers uncertainty in prediction by using a Bayesian regression technique called Gaussian Process. This approach is particularly useful when there are identical generating units (i.e., units with the same cost coefficients and start-up costs). They compared their methodology with a LR technique and found that the Bayesian Optimization approach performed better.

C. Ning and F. You [45] have proposed a data-driven adaptive robust optimization framework for the unit commitment problem that integrates wind power into smart grids. They used a Bayesian approach with a 6-bus and IEEE 118-bus system. The Bayesian Optimization method has been successfully applied to solve expensive black-box problems in engineering and machine learning, making it ideal for managing model-fitting problems [46].

With stochastic algorithms, acceptable levels of violation constraint probability are set so that the algorithm can identify the lowest cost solution for (re)dispatching, while guaranteeing a violation constraint probability that is lower than the fixed threshold.

H. Wu et al. [47] have highlighted how fixed thresholds such as Loss of Load Probability (LOLP) and Probability of Transmission Line Overload Accepted (TLOP) indicators can affect the rotating reserve costs. In particular, the rotating reserve costs decrease with the increase of the probability of losing the electrical load. This is because as the probability of the LOLP indicator increases, the ancillary services market can more precisely cater to the rotating reserve as Figure 3.1 (a) shows. The same principle applies to the TLOP, as increasing the accuracy of this indicator enables more cost-effective management of line congestion as is shown in Figure 3.1 (b). A mathematical formulation of LOLP is described in [26]. Specifically, the rotating reserve costs decrease as the probability of loss of electrical load increases.

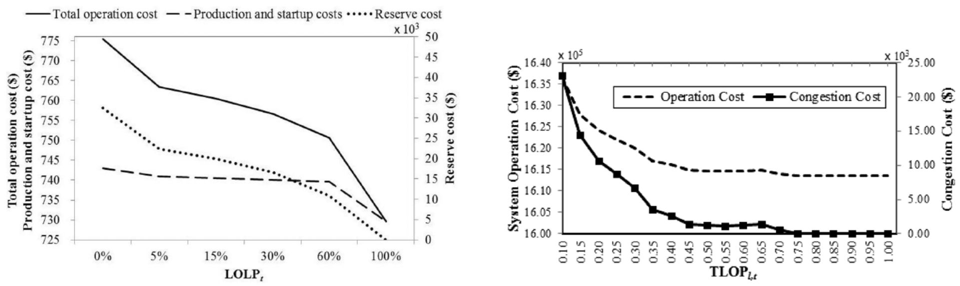


Figure 3.1. Behavior of the indicators [47]: (a) LOLP e (b) TLOP.

The LOLP and TLOP indicators are used as constraints in [48], which presents a

UC problem with uncertain loads and wind power, solved by a chance constrained two-stage stochastic programming formulation for the stochastic day-ahead scheduling.

The OPF based SCUC computational burden raises a lot considering the introduction of stochastic variables, with several operational scenarios. That means the computational timings raise too.

This is highlighted in [30], where a stochastic SCUC is described and tested on a model of the California power system with 225 bus, 375 lines and 130 generators. This paper presents a DC formulation and despite of the powerful hardware used, the computational timings of 5-15 h are not compatible with the Terna necessity. Papavasiliou et al. [30] show the several cases studied, considering about 1000 scenarios with N-1 security criteria, for each season of the year, as depicted in the Figure 3.2.

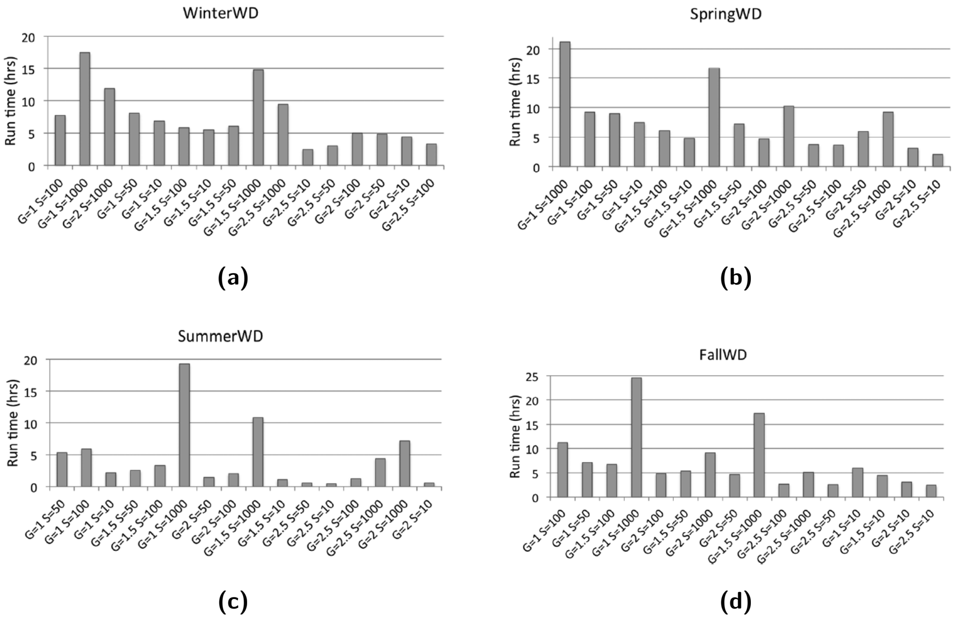


Figure 3.2. Study cases of [30], which formulates an DCOPF with UC, stochastic and considering N-1 security criteria: (a) winter, (b) spring, (c) summer, (d) fall.

Papavasiliou and Oren [49] compare in their paper two approaches for committing locational reserves: stochastic unit commitment and a hybrid approach of scenario-based security-constrained commitment which studied parallel algorithms developed for solving the resulting models, based on LR and BD. In [49] we can distinguish the different computational burdens of both the solution techniques proposed, by analysing the electrical network system of the State of California, which is composed of 225 buses, 375 lines and 130 generators. The running time of the Lagrangian relaxation algorithm ranges between 15.8 h for the fully serial implementation to 47.7 min in the fully parallel implementation, is also underlined how the marginal benefits of parallelization vanish beyond 15 processors (such as the BD solution). The advantage of the BD solutions is evident, the entire model requires 26.6 min to solve in a fully serial implementation, versus 14.8 min in a fully parallel implementation.

Table 3.2. Summary of the main SCUC resolution methods.

Method	Advantages	Weaknesses
Lagrangian Relaxation	It is able to process with non-linear constraints only by relaxing them. It can be decomposed in sub-problems.	It suffers from the existence of a duality gap.
Bender Decomposition	It can be separated into independent problem and sub-problem.	Low speed of convergence.
Mixed Integer Linear Programming	Is a powerful modelling tool, with a great ability to react in a globally optima solution.	It takes a long time compared to fast methods like heuristics. Is not good in treating large-scale problems.
Non-linear Programming	Good modelization of power generation characteristics.	It enhances the problem dimension and complexity.
Hybrid Meta-Heuristic	Is capable of handling indifferentiable cost functions and constraints.	Its finetuning is a negative point.
Bayesian Optimizzation	Very used to get an optimal solution with uncertainties. Useful to solve black-box problems and model-fitting problems.	It is really complicated to perform a modelization.

Table 3.2 summarized the main SCUC resolution techniques, showing a comparison between advantages and weaknesses.

3.3 Result of the research activity

In conclusion, with the increasing use of RESs such as wind and solar power, the power system's variability and uncertainty have significantly increased. Therefore, it has become essential to find effective ways to solve the UC and ED problems in a large-scale, non-convex, and uncertain program. Terna has aimed to employ a stochastic approach in its new MSD algorithm that can consider aleatory variables such as wind power and solar power, taking into account several operating scenarios characterized by their probability of occurrence. The stochastic variables are important in the new MSD algorithm, given that the contribution of the RESs is crucial to the National electrical grid reliability.

Various stochastic programming techniques have been proposed for managing uncertainties in the UC problem, including SP, RO, and CCO. The literature is divided into two categories: "two-stage" and "multi-stage" models. Furthermore, different approaches for decomposition have been proposed, such as scenario decomposition, unit decomposition, Lagrangian relaxation, Benders-like decomposition, and dual decomposition.

Moreover, new approaches such as Bayesian regression technique called Gaussian Process and data-driven adaptive robust optimization framework have been proposed to address the robust UC problem. These techniques have shown promising results in handling uncertainties and reducing the expected cost of the operating system while maintaining the electrical network's reliability.

It appears that currently there are no algorithms available in the literature that can effectively combine an ACOPF formulation with the UC and ED problems while considering stochastic variables. As a result, the next step is to conduct market research by meeting with potential suppliers and companies in order to identify possible solutions.

In practical industrial applications, solving the ACOPF problem with UC while explicitly modeling uncertainties (using a stochastic approach) is challenging, especially when considering the time constraints of electrical markets. Computational timings for solving this problem on a daily basis on a 380/220 kV electrical network (such as the Italian one) are not compatible with electrical market timings (30-60 min).

However, there are promising solutions available that can solve the SCUCED problem using either an ACOPF approach or stochastic methods. This suggests that TSOs should evaluate which of these features are more relevant for the power system they are operating and accept simplifications on the other part.

Non-linearity and non-convexity of the problem contribute to computation times that are still too long for market operations. This review concludes by summarizing the current state of knowledge regarding solutions to solve the SCUCED problem with stochastic variables to manage the strong penetration of RESs. The review compared the features and limitations of most of the algorithms proposed in recent scientific literature and shows that the DCOPF formulation is faster than the ACOPF.

This literature review is also useful for the Italian TSO to investigate the best solution for formulating a new algorithm potentially to be adopted in the Italian Ancillary Market, while explicitly modeling stochastic variables and voltage constraints.

It may be interesting to study in the future how to approach the analysed algorithms in a real case study like the Italian one. However, since it is not possible to consider a single algorithm that could contain the features of the new MSD algorithm, one of the following approaches could be considered as future work:

- resolution of the UC problem (using appropriate optimization techniques) can be achieved through the use of an outer iteration cycle with ACOPF (high accuracy with verified timing);
- integration of the DC problem with voltage estimation methods (low accuracy).

Table 3.3 summarizes the main features of the techniques proposed in the relevant scientific papers analyzed in this literature review.

Table 3.3. Summary of the articles analyzed.

Rif.	Power Flow AC	Power Flow DC	Security N	Security N-1	Stoch.	Voltage constraints	UC	ED	Study cases	Time
[30]	-	✓	✓	✓	✓	-	✓	✓	225 bus, 375 lines, 130 gen.	5-15 h 1000 scen.
[50]	✓	-	✓	-	✓	✓	-	✓	14, 118 bus	N.D.
[47]	-	✓	✓	✓	✓	-	✓	✓	31, 118 bus	41 s
[51] [52]	-	✓	✓	✓	✓	-	-	-	37, 118 bus	N.D.
[53]	-	✓	✓	✓	✓	-	✓	-	24 bus	25 s, 12 scen.
[54]	-	✓	✓	✓	✓	-	-	-	30, 118, 300 bus	159.78 s, 480 contingencies
[55]	-	-	✓	✓	✓	-	✓	✓	100 gen.	188.8 min
[56]	✓	-	✓	✓	-	✓	-	✓	1000 bus, 1100 lines, 180 gen.	N.D.
[57]	✓	-	✓	-	-	✓	✓	✓	6, 118 bus	0.13 s
[58]	✓	✓	✓	✓	✓	✓	-	✓	39 bus	N.D.
[22]	✓	-	✓	✓	-	✓	✓	✓	6, 118 bus	513 s
[49]	-	✓	✓	✓	✓	-	✓	✓	225 bus, 375 lines, 130 gen.	26.6 min
[59]	✓	-	✓	-	-	✓	-	✓	Polish grid, 14, 57, 118 bus	2.7 s
[60]	✓	✓	✓	✓	-	✓	✓	✓	24 bus	7.50 s, 120 contingencies
[40]	✓	-	✓	✓	-	✓	✓	✓	6, 79, 118 bus	110.17 s
[61]	-	✓	✓	✓	-	✓	✓	✓	1168 e 4672 bus, 1352 e 2704 UP	2-150 min
[41]	✓	-	✓	✓	-	✓	✓	✓	6, 24, 79, 96, 118 bus	8.5-14 400 s

Chapter 4

Projected Assessment of System Adequacy (PASA)

This chapter aims to analyse how RESs impact on the choice of scheduling maintenance for the conventional thermal power plants. In fact, the intermittent and unpredictable nature of wind and solar production has made the real-time balancing activity of electricity systems more complex and relevant due to the continuous matching of supply and demand.

Italy has an important potential for RESs, ranging from solar energy to hydro, geothermal, biomass and wind. In particular, U. Farinelli's article [62] emphasized how the RESs installed power was relevant since the year 2004, even if the Italian RESs installed power were a few fractions compared to the actual one.

Despite the great importance that European Union gives to the RESs power, NECPs (received by Italy according to [2]), a regulation analysed by P. Geoffron and L. De Paoli [63] and by K. Williges et al. [64], the evolution of RESs if not controlled may create consequences to the electrical network grid.

In literature, many papers describe the benefits and drawbacks about RESs. For instance, A. Gianfreda et al. [65] describe how the massive introduction of RESs in electricity markets have affected prices paid to procure balancing resources and, consequently, the costs charged to end users. Holttinen et al. [66] studied how wind power impacts on power system balancing, concluding that it is very important to take the variability of wind during wind integration studies. The article of F. Ocker and K.M. Ehrhart in [67] try to explain the “German Paradox”, which consists of a particular phenomenon where the German demand for balancing power did not increase in response to the immense growth of wind and solar energy production. The review of L. Hirth and I. Ziegenhagen [68] provides a study about three ways in which RESs and balancing systems interact, through the impact of RESs forecast error on balancing reserve, the supplying of balancing services by RESs and the incentives to improve forecasting provided by imbalance charges. In closing, several other studies have investigated the effect of RESs on power systems, see for instance Bigerna et al. [69] and [70], B. Moreno et al. in [71], A. Sapio [72] and finally I. Staffel in [73].

Nowadays a great evolution of RESs installed power is evident. According to the development plan written by Terna S.p.A [4] the wind and solar power installed during the 2020 are respectively of about 10 918 MW and 21 629 MW, as already described in Section 1.2. The RESs development grew drastically between 2010 and 2013, while this growth slowed down strongly over the last few years, as Figure 1.4 shows.

Moreover, the predicted solar power will grow up to another 50 GW within 2030, while the wind power of an additional 9 GW.

4.1 PASA model description

As described in the above the RESs impact the electrical grid because of several problems. A consequence about the RESs impact which has not already been analysed is the following: how do the RESs impact the maintenance schedule on thermoelectric power plants?

Other Projected Assessment of System Adequacy (PASA) analysis has been performed in literature, for instance J.P. Deane et al. [74] and D.C. Sansom et al. [75], but no one focus on the problem just proposed. In order to answer this question, a PASA analysis of the Italian electrical grid through the software PLEXOS has been performed.

The functions of the PASA simulation phase are mainly two:

- to create maintenance events for the subsequent simulation phases about “medium-term schedule” and “short-term schedule;
- to compute reliability statistics such as LOLP for the system.

The PASA algorithm uses results of an optimization that focuses on the balance of supply and demand in the medium-term. In multi-area models, PASA also calculates the optimal amount of reserve that should be shared between areas using the transmission network, like in the actual case of study. The Italian market areas analysed are the following: North, North Central, South Central, South, Calabria, Sicily and Sardinia.

Briefly, PASA algorithm assigns the number of maintenance operations on power plants by maximizing the region capacity reserve of the year simulated. This is possible because the algorithm considers the power plants’ availability with respect to the electrical load peak.

The algorithm always runs in annual steps across the whole planning horizon, for this study case the time horizon considered is the year 2022, which runs for 365 days considering an interval length of 1 hour.

Since the aleatory variables that have been taken into account are for instance the wind and solar power, a stochastic PASA simulation has been performed considering ten variable sample draws while a parallel Monte Carlo stochastic method is implemented. The ten variables used by the algorithm refer to the hourly RESs power value and the power electrical demand value registered during each hour of each year between 2007 and 2016.

4.2 PASA model and methodology

In order to run the PASA algorithm through the software PLEXOS, different data have been given as input to the model. In this section, we analyse the input data, with the purpose to understand better the PASA model.

A file containing all Italian power plants whose fuels are biomass, fossil gas, fossil hard coal, fossil oil and hydro has been uploaded into the model. Each power plant has been assigned to the respective Italian region analysed.

Each generator has been assigning their technical constraints:

- power plant on/off status;
- "Generator Max Capacity": which defines the nominal rating of the generating units;
- "Generator Min Stable Level": it is the minimums stable generation level of each generating unit;
- "Generator Min Load": setting a lower bound on the generation from the facility in each dispatch interval regardless of the unit commitment;
- "Generator Pump Load": applying to pump storage generators and as an input property is the maximum megawatt load drawn per unit while in pump mode;
- "Generator Min Pump Load": it is the minimum per unit load when the generator is in pump mode.
- "Generator Maintenance Frequency": it is the sets of the number of maintenance events that will occur of the given type each year;
- "Generator Forced Outage Rate": setting the expected level of unplanned outages. For instance, the Forced Outage Rate above of 2.5 % implies that on 8760 h of the year, the generator will be out of service $0.025 \times 8760\,\mathrm{h} = 219\,\mathrm{h}$
- "Generator Mean Time to Repair (MTTR)": it is used as the location parameter for several of the functions that generate outage duration samples for both forced and maintenance outages. For instance, if the MTTR is 36 h and considering a Forced Outage Rate of 219 h, will be on average $219/36 = 6$ random outage events.

Regarding the electric charge, we considered a regional load model. In fact, we considered the load for each electrical market areas, which corresponds to the Italy geographic regions or a group of them (North, North Central, South Central, South, Calabria, Sicily and Sardinia). Since Italy ensures also the electrical interconnection with neighbouring countries, the net transfer capacity exchanged with Greece, Corsica and Montenegro has been modelled as transfer capacity exchanged with a region directly linked to Italy. Instead, all the Northern Italian Borden has been modelled as a macro area which consider the interconnection between France, Switzerland, Austria and Croatia.

The Figure 1.1 (b) shows the interconnection with the neighbouring countries.

The load input file has been calculated for each Scenario examinated, in particular we considered the "residual" electrical load demand, defined as:

$$L_{net}^{C} = L_{gross} - P_w - P_s - P_b - P_g - P_h - P_{other} \tag{4.1}$$

where L_{gross} is the total Italy's load demand, P_w is the power which came from the wind power plants, P_s is the power from solar power plants, P_b is the power from biogas power plants, P_g is the power from geothermal power plants, P_h is the power from hydro power plants and P_{other} is the power produced by small thermal power plants, which not participate to the Italian Ancillary Market (<10 MVA).

The result of (4.1) is L_{net}, representing the electrical "residual" demand that thermal power plants must meet. In few words is the electric power which is the exchange during the auxiliary market.

The (4.1) changes considering the different scenario analysed:

- Scenario A: a stochastic load without the RESs has been performed. In this Scenario the contribution of the all RESs like solar, wind, hydro, biomass and geothermal energy to the electrical power demand has not been take into account. Thus, the formula which calculates the "residual" electrical load demand is:
$$L_{net}^{A} = L_{gross} - P_{other} \tag{4.2}$$
- Scenario B: in this Scenario the stochastic load has been calculated without the Variable Renewable Energy Sources (VREs) like wind and solar energy. So, in this case the other RESs have been considered, and the formula turns in:
$$L_{net}^{B} = L_{gross} - P_b - P_g - P_{other} \tag{4.3}$$
- Scenario C: this last Scenario considers the stochastic "residual" electrical load calculated taking into account all the RESs, therefore the formula is the one described in equation (4.1).

Each Scenario has been performed for every market areas, analysing how the schedule of maintenances of power plants modifies depending on the three cases of study.

As soon as the simulation is performed, the PLEXOS software enables us to analyse some outputs from the PASA simulation. The main outputs are described in the following bullet list:

- "Region Capacity Reserves": is the reserve margin of electrical capacity, calculated for each area of the model and defined as follows:

$$CR = \sum_{i=1}^{n} GC_{rated} - \hat{L} - M_{discret} - M_{distrib} - EFO - NCI \tag{4.4}$$

  Where CR is the Capacity Reserves, GC_{rated} are the Generators Rated Capacity which is the number of installed units at the generation facility, $\hat{L}$ is the Region Peak Load which is the maximum load in that period, $M_{discret}$ is the maintenance that is defined by the Generator Units Out property, $M_{distrib}$

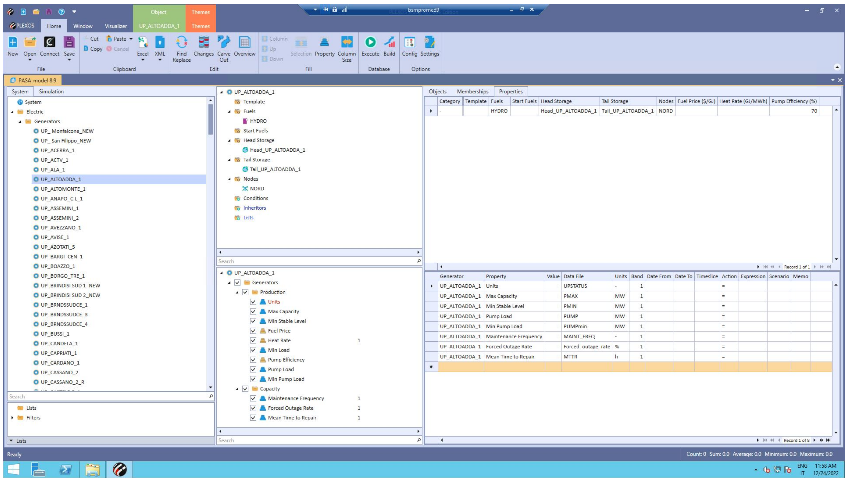


Figure 4.1. Screenshot from the software PLEXOS, in which we can see how a typical power plant has been modelled.

is the maintenance allocated by the optimization algorithm in order to level the regional Capacity Reserves, EFO is the Expected Forced Outage which is calculated as the total sum of the multiplication between each Generators Rated Capacity and the Generator forced Outage Rate, NCI is the Region Net Capacity Interchange, which is the region's notional net export capacity, taking into account the amount of capacity shared across the line;

- "Region Maintenance Factor": as an output, the Maintenance Factor reports the optimal values calculated by PASA, whose profile is based on the inverse of the Capacity Reserve;
- "Generator Distributed Maintenance": is already defined above in the formula equation (4.4);
- "LOLP": is the Loss of Load Probability, defined as the measure of the probability that demand will exceed the capacity of hte system in a given period;
- "Loss of Load Expectation (LOLE)": is the Loss of Load Expectation index and is calculated directly from the LOLP as $LOLE = LOLP \times t/24$, where t is the number of hours in the PASA period;
- "Units Out": is the output file which shows the on-off production unit for each hour of the year, considering the Forced Outage Rate and facility maintenance profile.

Figure 4.1 shows a view of the software PLEXOS, in which we can see how a power plant is modelled, in particular we can observe on the left of the figure a small list of the power plants considered and on the right the characteristics used to model the power plants.

Chapter 5

PASA simulation results

This chapter summarizes the outcomes from the analysis of the Scenarios. Three scenarios have been simulated and three different solutions have been obtained, which express the RESs' importance about the scheduled thermal power plants outages.

Figure 5.1 (a) shows how the total Italian load demand changes with regard to the three types of scenarios analysed. In particular, Scenario A and Scenario B are quite similar, since the only difference is that Scenario B does not take into account the VREs contribution. This similarity is notable also in equations (4.2) and (4.3), where the only difference is that in (4.3) is taking into account P_b (biogas) and P_g (geothermal), which give a small contribute to the "residual" load calculated in Scenario B. That is the reason why the curve in Scenario B is slightly smaller than in Scenario, as shows in Figure 5.1 (a).

However, Scenario C is particularly interesting as the difference between the other two scenarios is significant. Indeed, the "residual" demand load calculated using the equation (4.1) is the lowest because a notable contribution to the demand load is covered by the VREs.

This analysis also influences the expected number of power plant maintenances, as illustrated in Figure 5.1 (b).

Since load demand is higher in the summer (i.e. July) than in other months, the PASA algorithm prefers to assign power plants' maintenances when the load is the lowest. In fact, the number of planned outages are targeted in April, May and August for each Scenario.

This is the reason why the number of planed maintenances is higher during the month of May (49 planed outages for Scenario A, 51 planed outages for Scenario B and 45 planed outages for Scenario C). Currently, during this month a low electrical demand is recorded, so that the RESs and the remaining thermal power plants can guarantee an adequate power reserve.

The grey curve, which refers to Scenario C, shows a similar pattern in comparison to the other two scenarios. The only difference is that the planned outages are better distributed during the months with low electricity demand (i.e. April, May and August). In fact, we can see 44 planed outages in April, 45 planed outages in May and 43 planed outages in August. This better distribution depends on the contribution of RESs in electricity power Scenario, which are important during these

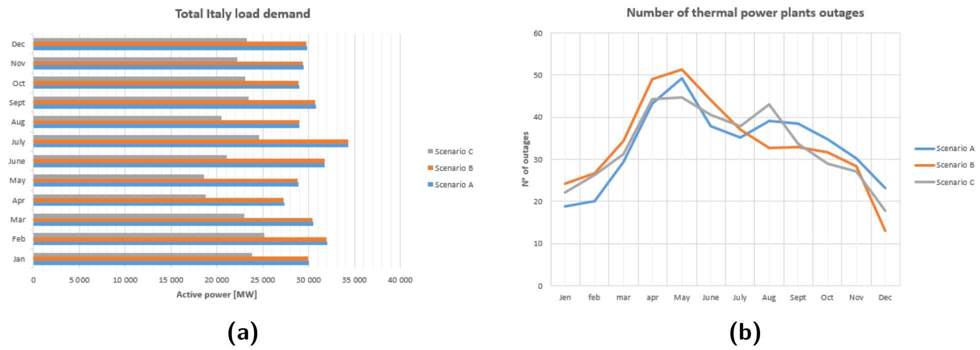


Figure 5.1. The outcomes from the three scenarios simulations: (a) the total Italy demand considering the three scenarios simulated; (b) the number of thermal power plants outages for each Scenario simulated.

months.

While Italian total load demand is very similar between Scenario A and Scenario B, the curves representing the number of power plants maintenances are not similar at all. This difference is caused by the Generator Forced Outage Rate and the Generator Maintenance Frequency as input for each thermal generator (see Section 4.2), which cause a random result for each simulation. This “aleatory” simulation is characterized by the PASA algorithm objective function, which assigns the number of power plants’ maintenances by maximizing the region capacity reserve of the year simulated.

Chapter 6

Conclusions

This essay aims to analyse the state of art of the OPF algorithms also taking into account stochastic variables i.e. wind and solar generation.

Actually, it seems very challenging solving the ACOPF problem with UC in industrial practical applications. In fact, the computational timings for solving the described problem with a daily horizon, on a 380/220 kV electrical network (like the Italian one) are not compatible with the electrical market timings (30-60 min). There is no evidence found about an algorithm which takes into account all the requirements expressed by Terna in Section 3.2.

In conclusion of this research, it would seem that in literature there are no algorithms which can combine an ACOPF formulation with UC and EC problem considering the stochastic variables.

In particular, it appears very interesting to study applications of SCUCED algorithms with stochastic variables in real-world cases, as constraints on voltages and different scenarios may cause the algorithm to diverge or have excessively long resolution times. This leads to the possibility of further investigating the topic in the future, by studying which resolution strategies can be considered and understanding at what hardware level we need to aim to solve the algorithms within the expected MTU.

Secondly, the work done during the last year of PhD aims to analyse the planned maintenance of thermal power plants through a PASA simulation using the PLEXOS software, where three different scenarios are realized. The scenarios considered are the following: Scenario A in which the RESs contribution is not taken in account, Scenario B where the only VREs contribution is taken into account and Scenario C in which all the RESs contribution is considered.

The simulations performed show how the RESs contribute to the number of maintenance of thermal power plants significantly. Indeed, in Scenario A and Scenario B the maintenances are all concentrating in the month of May, while the outputs of Scenario C show how the RESs can guarantee sufficient power reserve, thus the maintenance of thermal power stations may be better distributed over the months with a lower load demand, this is because during these months there is a greater contribution from RESs, thus ensuring greater load coverage.

Finally, the PASA simulation showed that RESs can contribute to a better distribution of maintenance for thermal plants. However, in future research, it could be studied the economic impact of these maintenance activities on MSD, taking into account their outage time.

In conclusion, this PhD research aimed to demonstrate how RESs, and hence stochastic variables, are becoming increasingly relevant, impacting the safety and stability of the national power system. Therefore, it is important to consider the numerous scenarios in which stochastic variables can operate, so that Terna can procure rotating reserve with increasing precision, in order to ensure the stability of the Italian power grid in the event of any type of contingency.

Appendix A

Other research activities

During these three years of PhD side research activities were focused on other research activities like the study and sizing of the internal Medium and Low Voltage Network (MLVN) of the future fusion power plant called “DEMOnstration Power Plant (DEMO)”.

If nuclear fusion were to be developed to the point of being used for the production of electricity, it would almost certainly be classified as RESs. For this reason, studying the DEMO plant has been interesting, as a nuclear fusion plant could certainly impact the current configuration of electricity markets in the future.

In particular, this appendix will describe the three types of studies that have been conducted on the DEMO electrical distribution grid, which dealt with:

- a first sizing of the electrical components like power transformers and cables of the DEMO MLVN;
- a study of the DEMO High Voltage Network (HVN), in terms of connection with the external grid and the analysis of the different kind of Point Of Delivery (POD);
- an electrical load parametric evaluation and a sensitivity analysis of the most relevant electrical loads.

All the simulation have been performed by the software DIgSILENT PowerFactory.

A.1 EUROfusion project

The European Union has defined a long research path, whose goal is to generate electricity by the thermonuclear reaction for the first time within 2050 thanks to DEMO reactor. This path is summarized in the “European Research Roadmap to the Realisation of Fusion Energy” [76].

In order to reach the tasks described in the roadmap, the European Union has established a consortium named “EUROfusion” which is made up of 26 EU members plus Switzerland. Today, this consortium collaborates with organizations from all over the world, including China, South Korea, India, Japan, Russia, the United States.

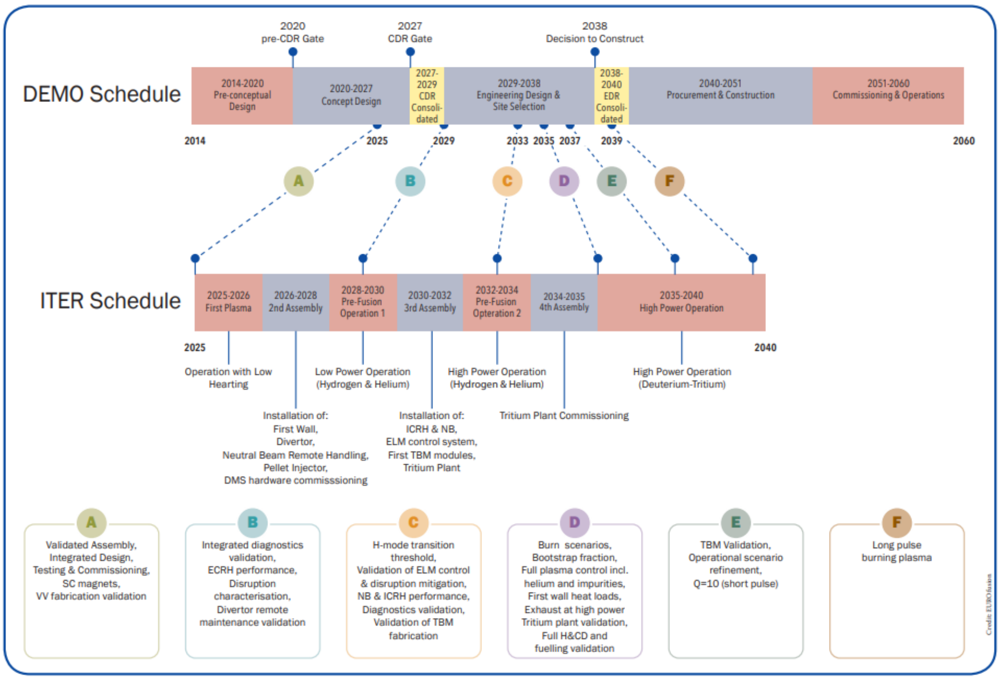


Figure A.1. Schedule of EUROfusion roadmap.

For each member of EUROfusion a research institute called "Programme Manager" has been identified called "Programme Manager", for instance in Italy the Programme Manager is "Agenzia nazionale per le nuove tecnologie, l'energia e lo sviluppo economico sostenibile (ENEA)" of Frascati.

The program for the fusion is summarized in Figure A.1.

The first step of the EUROfusion project is to build International Thermonuclear Experimental Reactor (ITER), which is a tokamak currently under construction in France in the city of Cadarache.

The main goal of ITER is to produce plasma fusion for the first time using deuterium and tritium as fuel and secondly to demonstrate the fusion reaction feasibility for a given period of time [77].

The fusion reactor DEMO is the successor of ITER, in fact if ITER aims to demonstrate the feasibility of the nuclear fusion reaction, DEMO aims to demonstrate the feasibility to exchange the electrical power generated by the nuclear fusion reaction with the external electrical grid.

Even if DEMO is greater than ITER, DEMO is organized in the same way. According to the EUROfusion map, the energy produced by DEMO will be around 500 MW, three or four times less than a nuclear fission reactor, however, useful to demonstrate the feasibility of a nuclear fusion power plant.

Table A.1 and Table A.2 show the technical characteristics of both fusion reactor power plants ITER and DEMO. Figure A.2 shows how the future worksite of DEMO should be.

Table A.1. Technical characteristic of ITER [78].

Characteristics	Values
Building height	24 m
Building width	30 m
Building weight	23 000 t
External radius of plasma	6.2 m
Internal radius of plasma	2 m
Input power	620 MW
Output power	$\approx$ 700 MW
Plasma current	15 MA
Toroidal magnetic field	11.8 T
Fusion time	$\geq$ 400 s

Table A.2. Technical characteristic of DEMO [79]

Characteristics	Values
External radius of plasma	9.0 m
Internal radius of plasma	2.9 m
Plasma current	18 MA
Toroidal magnetic field	5.9 T
Output power	$\approx$ 500 MW
Fusion power	2000 MW
Fusion time	7200 s
Plasma energy	1.181 GJ

Figure A.2. Illustration of the DEMO worksite [78].

A.2 DEMO technical characteristics

Due to its operational phases, DEMO is considered by the external electrical grid pulsed electrical load, since it works between the production phase and a rest phase.

The tokamak operations are based on the heating of a plasma up to temperatures at which it is self-sustained by the fusion processes induced by the ion thermal motion. In DEMO, the plasma heats up the surrounding structure, the tokamak Breeding Blanket (BB), and the fluid used to cool down the BB can drive a turbine generator through proper heat exchangers.

The plasma must not be in contact with the internal Vacum Vessel (VV) due to its high temperatures, that are around 150 M°C reached by opportune Heating and Current Drive (HCD) systems. For this purpose, the plasma is confined inside the VV thanks to some powerful solenoids which crate an electrical field in order to confined it.

The operational phases of every tokamak are the following, so the same for DEMO:

- “pre-magnetization” phase: first of all the superconductive magnets are energized to attain a suitable value of magnetic flux into VV and the pumps prepare the vacuum into the chamber. The pre-magnetization is typically executed by supplying the superconductors at rather constant voltage, producing an increasing current and resulting in an increasing power demand from the grid;
- “breakdown” phase: it is the shortest phase (about 1 s) but also the most critical phase from the power supply point of view. The plasma initiation requires high-power pulses in several superconducting coils. The effective presence of the plasma in the tokamak vessel starts in this phase;
- “plasma ramp-up” phase: in this phase, the plasma current is progressively increased by the coils and HCD sources. The ramp-up must be slow in order to keep the plasma under control;
- “heating flat-top” phase: all the HCD sources are used to heat up the plasma until fusion temperature and conditions are reached;
- “burn flat-top” phase: DEMO produces energy thanks to the nuclear fusion reactions. Ideally, during this phase, the fusion reactions taking place at a sustainable rate guarantee the self-sustainment of the plasma. This phase is very long, about 7200 s;
- “plasma ramp-down” phase: the plasma is gradually switched off, maintaining its control by coil and HCD power.
- “dwell-time” phases: it is the time required after the pulse to bring DEMO to a condition stable enough to start a new pulse and to create an adequate vacuum inside the plasma chamber.

The heat produced by the plasma fusion must be transferred to a turbine linked with a electrical generator able to transform it into electrical energy with maximum possible efficiency and reliability. In the present status of the DEMO project, two alternative solutions are considered as basic fluid to cool down the BB: water and helium. In particular the way to cool down the BB are called:

- Water Cooled Lithium Lead (WCLL);
- Helium Cooled Pebble Bed (HCPB).

This pulsed behaviour may introduce specific problems for the Balance of Plant (BoP). First, discontinuous operations would be damaging to the turbine, then the variable flow of the expected huge powers may let some instabilities arise into the external grid that could even refuse or limit the connection. This problem is even more critical because of the relevant reactive components in power.

In order to reduce the output power fluctuations, an intermediate buffer system could be inserted between the and the heating transfer system and the turbine. Therefore, two different approaches are under evaluation:

- "direct coupling cycle": where the heating transfer system and the turbine are direct coupled;
- "indirect coupling cycle": where an energy storage system is coupled between the heating transfer system and the turbine.

The DEMO electrical layout is described in Figure A.3, which shows the five main subsystem constituting the DEMO electrical power plant:

- Turbine Generator: to generate the gross of electrical power;
- HVN: to connect the DEMO power plant to the external electrical grid;
- MLVN: to deliver the electrical power from the HVN to the medium and low voltage electrical components;
- Coil Power Supply and fast discharge units: to supply the needed voltage and current to the superconductor coils for the plasma formation, and its sustainment and control during the pulse;
- HCD: to provide the supply of the devices for the HCD system.

A.3 Object of work

The research study of the DEMO MLVN has been performed thanks to the software DIgSILENT PowerFactory.

All the simulations have been performed by the software PowerFactory DIgSILENT.

The DEMO's electrical loads can be organized into several sub-systems, that are summarized as follows:

- Magnet System (MAG);
- Tritium, Fueling, Vacuum (TFV);

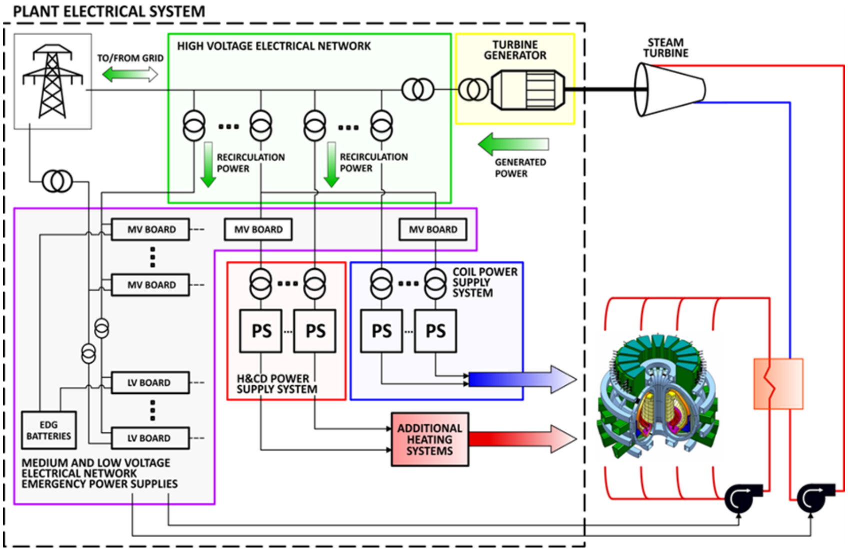
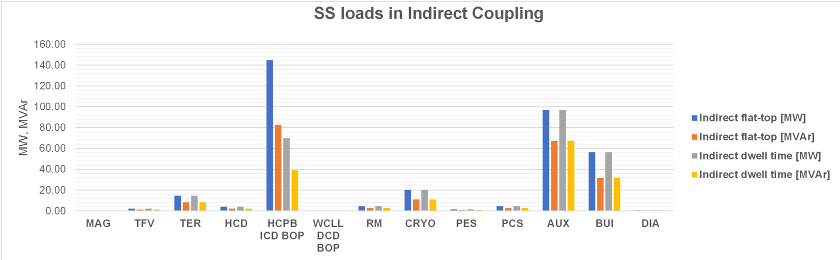


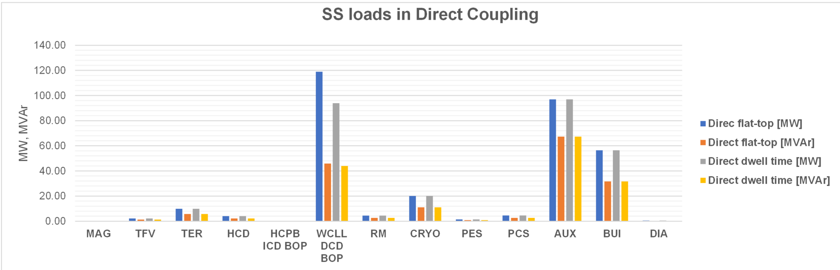
Figure A.3. Simplified block scheme of the EU DEMO Plant Electrical System.

- Helium Cooled Pepple Bed (TER.HCPB);
- Water Cooled Lithium Lead (TER.WCLL);
- HCD;
- Helium Cooled Pebble Bed Indirect Coupling Design Balance of Plant (HCPB ICD BOP);
- Water Cooled Lithium Lead Direct Coupling Design Balance of Plant (WCLL DCD BOP);
- Remote Maintenance System (RM);
- Cryoplant and Cryodistribution (CRYO);
- Plant Electrical System (PES);
- Plant Control System (PCS);
- Auxiliaries (AUX);
- Buildings (BUI);
- Diagnostics (DIA).

In Figure A.4 an estimation of the active and reactive power of each sub-system is summarized. We can see a markable difference when the scenario analysed change between the direct coupling cycle and indirect coupling cycle, in particular Figure A.4 (a) considered the HCPB cooling system during the indirect coupling while the A.4 (b) considere WCLL cooling system during the direct coupling.



(a)



(b)

Figure A.4. (a) Load comparison between a weekday 10/04/2019 and Easter day 21/04/2019. (b) Italy annual load demand profile from 2005 to 2021.

A.3.1 Estimation of DEMO's electrical component sizing

For the design of the electrical scheme, a complete model of the distribution system has been implemented in DIgSILENT PowerFactory, with reference to the steady state loads, in order to perform power flow calculations to check the correct sizing of the components, considering the different phases of operation (flat-top and dwell time) in the two coupling configurations. Figure A.5 shows a summary of the criteria e procedures used to sizing the DEMO MLVN.

The criteria and limits for the components design/sizing used are:

- limit on maximum voltage drop in the distribution system during operation accepted: 4 %;
- criterion for power transformers size check: power lower than the nominal value of the apparent power, without any possible overload;
- criterion for cables size check: current lower than the nominal thermal current limit, chosen among the possible current limits;
- criterion for voltage level choice for each load: loads with a nominal power lower than 200 kW are supplied in low voltage (<1 kV); loads with a nominal power superior or equal to 200 kW are supplied in medium voltage (>1 kV);
- criteria for splitting loads on different electrical sub-stations, type of load specified inside the Electrical Load List (ELL) (e.g. Safety Important Classified (SIC) and Ordinary Load (OL)), the distances between the buildings where loads are located and the electrical sub-stations hypothesized, referring to the most updated site layout.

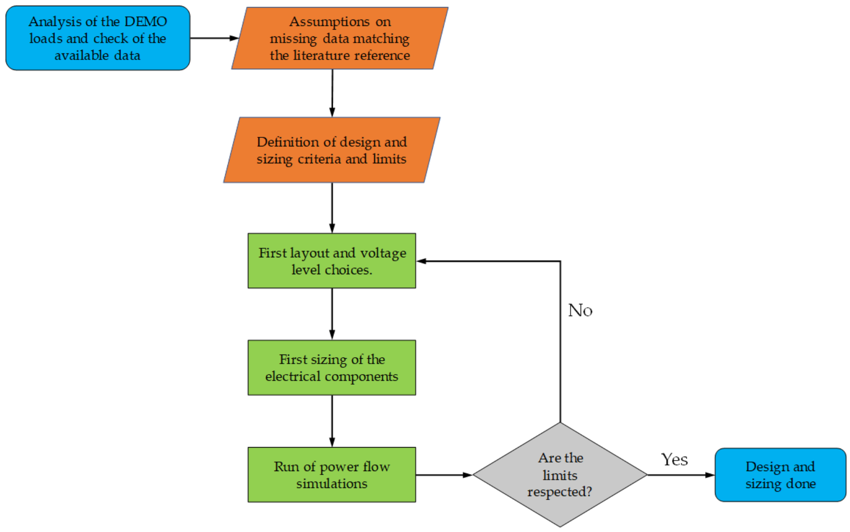


Figure A.5. A flow chart which summarizes the methods and procedures used to sizing the DEMO MLVN

Another important step for first sizing of the DEMO electrical grid is the load characterization, consisting in the evaluation of DEMO ELL, a document where fis characterzed by:

- load type: SIC, Investment Protection (IP) or OL;
- phase: number of the electrical phase of the load;
- voltage level: nominal supply voltage of the load;
- rated power: nominal active and reactive power of the load;
- rated power factor.

The results of the power flow analysis on PowerFactory checked correctly the power transformer and cables which have been used to performed the simulation. The electrical data of these components are summarized in Table A.3 about the power transformer considered and Table A.4 about the power cables considered into the simulation.

A.3.2 The DEMO High Voltage switchyard

DEMO HVN is the part of power plant electrical system connecting DEMO to the external electrical grid.

The possible options for the connection scheme of DEMO HVN that have been investigated are the following:

- single POD: the most favoured option, implying that all the electrical subsystem shown in Figure A.3 are connected to the same node of the High Voltage European Transmission Grid. In this case, DEMO would fall into the category of power generating/demanding facilities, in this configuration the design of

Table A.3. Design choices on power transformers.

Transformation ratio	**Size [MVA]**	**Number**
400±1.25%×12/22 kV	150	6
22±1.25%×4/6.6 kV	3.75	13
22±2.5%×4/6.6 kV	7.5	1
22±1.25%×4/6.6 kV	40	9
22±1.25%×4/6.6 kV	20	6
6.6±2.5×2%/0.4 kV	3.150	9
6.6±2.5×2%/0.4 kV	0.315	9
6.6±2.5×2%/0.4 kV	0.630	5
6.6±2.5×2%/0.4 kV	1.250	1
22±2.5×2%/0.4 kV	3.150	1

Table A.4. Design choices on power cables.

Voltage level [kV]	**Rated current** [kA]	**Section** [mm^2]
0.4	0.035	5G4
0.4	0.060	5G10
0.4	0.105	5G16
0.4	0.154	5G25
0.4	0.550	1×240
0.4	0.620	1×300
6.6	0.690	3×400
6.6	0.760	3×500
6.6	0.850	3×630
6.6	0.930	3×800
6.6	1.010	3×1000
6.6	0.312	3×120
6.6	0.351	3×150
6.6	0.396	3×185
6.6	0.460	3×240
6.6	0.126	3×25
6.6	0.517	3×300
6.6	0.187	3×50
6.6	0.229	3×70
6.6	0.275	3×95
6.6	0.313	3×120
22	0.453	3×150
22	0.612	3×240
22	0.813	3×400

Table A.5. Advantage and disadvantage about the three POD configurations studied.

POD configuration	Advantages	Disadvantages
Single	Simple implementation	Stress on the turbine generator due to power spikes. Problems with the operation of the generator
Double case 1	Pure generation node. No stresses on the turbine generator from the power spikes	Impact of the power spikes on the operation and integrity of the electrical grid
Double case 2	No stresses on the turbine generator from the power spikes	Pure generation node only in case of indirect coupling. Mixed generation/demand node in case of direct coupling.

HVN cannot be made as in ITER, due to the presence of the generator on the same node;

- double POD case 1: in this case the internal HVN should start by two different PODs, to supply all the subsystems included in DEMO electrical power plant. This implies that the HVN should have a section on POD dedicated only to the loads, which can work as ITER HVN, and a second section on a second POD dedicated to the turbine generator;
- double POD case 2: two connection nodes of the HV European Transmission Grid are used, one dedicated to the turbine generator and the MLVN loads and the other dedicated to HCD and the coil power supply system.

These three options present several features that are summarized in Table A.5 and their block scheme are illustrated in Figure A.6.

A.3.3 The electrical load parametric model

The aim of these work is to simulate the operational of the MLVN and HVN, in order to checking the sensitivity of the design and sizing to the assumption and randomness of input data. The final task is to evaluate the variation of the electrical power exchange between the DEMO power plant and the external grid. The simulation has been performed by using the Monte Carlo algorithm. Each load have been assigned an uncertainty level around the rated power level and around the utilization and contemporary factor value. In particular the uncertainty level define a normal distribution following the Gaussian curve.

The data used as input for the parametric model have been defined starting from the new information collected in the ELL, in terms of active power and of utilization and contemporary factors, to which uncertainty coefficients were assigned.

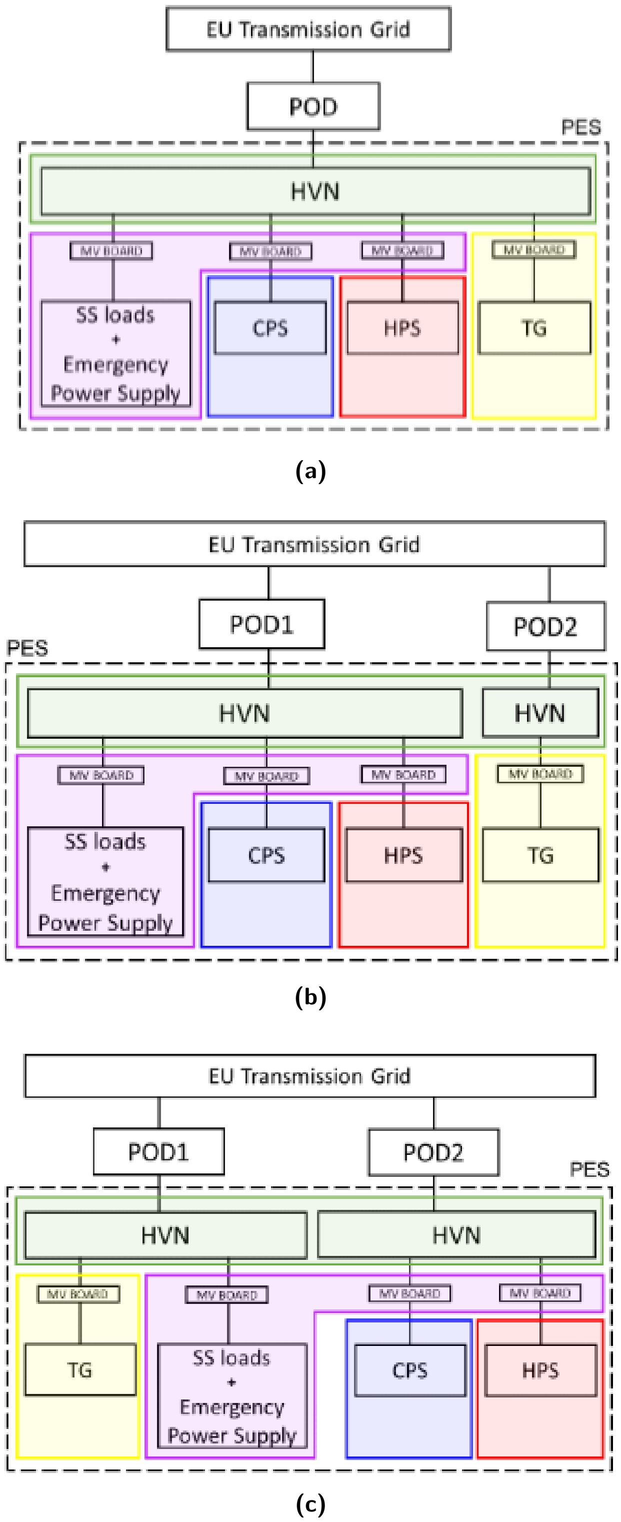


Figure A.6. (a) DEMO HVN configuration with single POD. (b) DEMO HVN configuration with double POD case 1 (c) DEMO HVN configuration with double POD case 2.

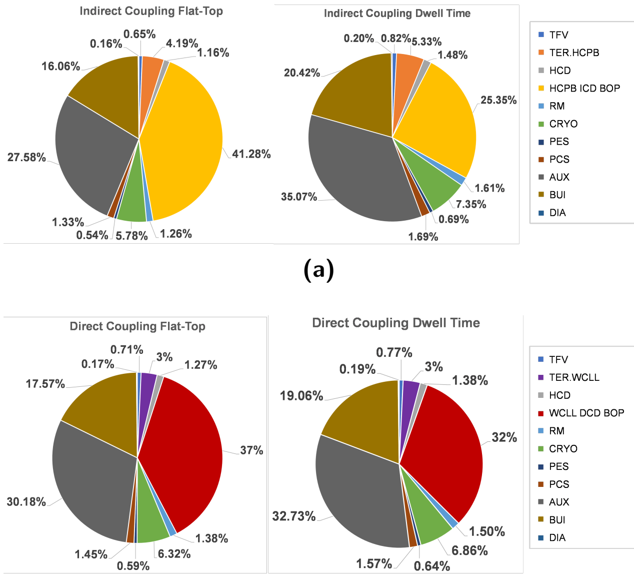


Figure A.7. (a) Subsystem weights on total power in indirect coupling configuration. Subsystem weights on total power in direct coupling configuration.

Table A.6. Main load clusters and uncertainty coefficients associated to the power values.

Cluster	**Uncertainty coefficient on power values**
Pumps	5% 20%
Special loads	50-100% 30% for CRYO 20% for AUX
Lumped loads	60-85%
Cubicles, panels, distribution boards...	50-100%

The assessment of these coefficients was based on several criteria, primarily the clustering of loads according to the weight of the power required from each subsystem per coupling configuration and plasma phases. In particular Figure A.7(a) shows the subsystems weights considering the indirect coupling, while Figure A.7(b) shows the subsystems weight considering direct coupling instead.

On the basis of these assumptions, uncertainty coefficients have been assigned to the various load clusters, also taking into account the reliability of the data source. Table A.6 reports, as an example, the uncertainty coefficients in terms of percentage with the meaning that the active power can vary within a range defined by that value.

The power absorption profile was modelled according to a normal distribution, whose mean value μ was assumed to be equal to the active power value given in the ELL and whose standard deviation σ was assumed to be equal to the uncertainty coefficient. Similar assumptions were made for the utilization and contemporary

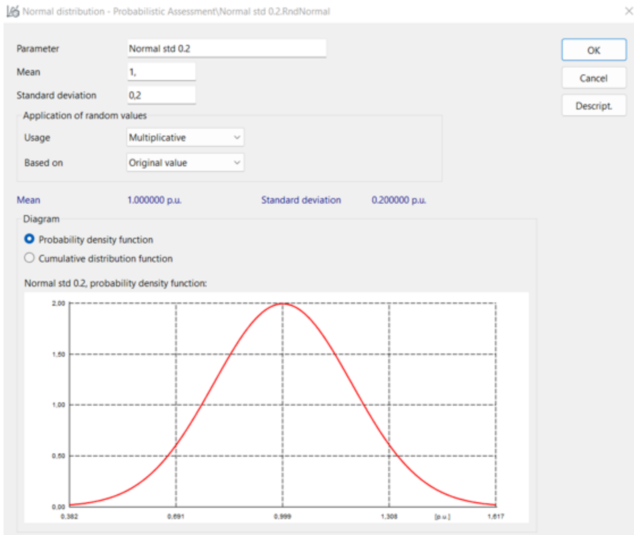


Figure A.8. Normal distribution associated with an uncertainty coefficient of 20%.

Table A.7. Case 1 output results of the simulation about the DEMO parametric model.

CASE 1	Active Power [MW]	Reactive Power [MVAr]
Indirect Flat-Top	351.27 ± 33.21	260.10 ± 31.43
Indirect Dwell-Time	275.99 ± 34.06	207.11 ± 31.96
Direct Flat-Top	322.58 ± 34.74	217.81 ± 33.22
Direct Dwell-Time	296.36 ± 34.68	212.35 ± 32.85

factors. Figure A.8 shows how the normal distribution curve has been implemented on PowerFactory, considering an uncertainty coefficient of 20%.

The results are obtained by simulating a "Multiperiod Probabilistic Power Flow", with the objective of obtaining a distribution of the active and reactive power profile exchanged with the grid. The Table A.7 and Table A.8 show the results of this analysis.

Two case study are considered:

- "Case 1": uncertainty value applied to power values;
- "Case 2": uncertainty coefficient applied to both power values and contemporary and utilization factors.

However, the comparison of the results indicates that there are no significant differences between Case 1 and Case 2 in terms of power requirements. For this reason, a sensitivity analysis has been performed running several Probabilistic Power Flow simulations, through the following steps:

- identification of the subsystems with the highest rated power, which are: AUX, HCPB, WCLL and BUI;
- assignment of normal distributions to the power of the loads of the mentioned subsystems;

Table A.8. Case 2 output results of the simulation about the DEMO parametric model.

CASE 2	Active Power [MW]	Reactive Power [MVAr]
Indirect Flat-Top	352.12 ± 32.86	260.93 ± 31.05
Indirect Dwell-Time	276.92 ± 32.21	208.02 ± 30.36
Direct Flat-Top	321.24 ± 33.41	216.55 ± 31.55
Direct Dwell-Time	295.30 ± 32.79	211.43 ± 30.91

- performing of Probabilistic Power Flow simulations on the most significant subsystems individually.

A linear regression analysis of the new values was then conducted and the R2 coefficient has been calculated, in order to evaluate the impact of the variation of the installed power of specific subsystems on the total required power. The results are also interesting with reference to design choices for both secondary substations and cable cross-sections.

Analyzing the value of R^2 allows us to assess the error in considering the dependence of the power variation to be linear. The error is small in any of the cases considered, so it is possible to refer to the angular coefficient of the straight line approximating the curve, to compare the dependence of the total power required to the grid on the individual parameters.

The charts from Figure A.9 to Figure A.12 report the linear regression and trendline showing the dependency of the active and reactive power values of the external grid from the active and reactive power values of the main subsystems considered.

A.4 Conclusions

In this appendix a parallel study conducted on the future fusion power plant DEMO during the PhD period is shown.

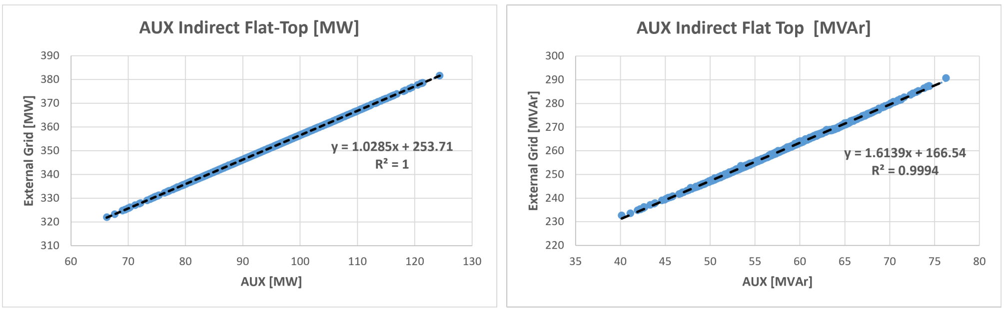
In particular, the study on DEMO MLVN shows a first sizing and design of the main electrical components like power transformer and cables. Moreover, the study on the HVN presents three typologies of POD, showing advantages and disadvantages, which are: single POD, double POD case 1 and POD case 2.

Secondly, the progress of the preliminary analysis on possible schemes of a part of the MLVN has been presented. Afterwards, the activity of updating DEMO Electrical Load List (on the basis of a reasonable extrapolation from ITER Project, including information on IP and SIC loads) and a probabilistic power flow study was performed, thanks to the Monte Carlo method. The simulations allowed us to preliminary assess the total power profile required by DEMO from the European grid.

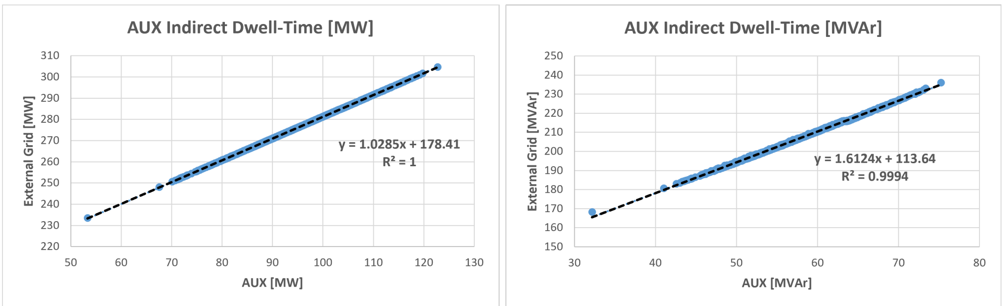
A comparative analysis of the results shows that the overall power exchanged with the grid is affected by the uncertainties related to the assumptions made about the loads. A sensitivity analysis allowed us to assess how the probabilistic profile changes at the point of connection with to grid, by varying the assumptions on the random coefficients of the input variables. The main steps of the study are the following:

- identification of the subsystems with the highest rated active power;
- assignment of normal distributions to the value of the rated active power of each load included in such subsystems;
- performing of probabilistic power flow simulations on the most significant subsystem individually.

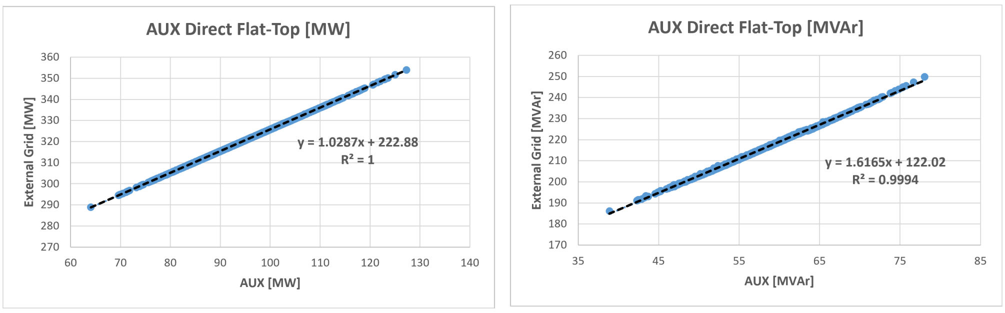
This simulations allowed assessing the level of sensitivity of the total power exchanged with the external grid to the assumptions made on the internal subsystems, underlining the well-known importance to have a good level of knowledge and certainty on the loads, in order to face the issues related to the interface between DEMO and the external grid.



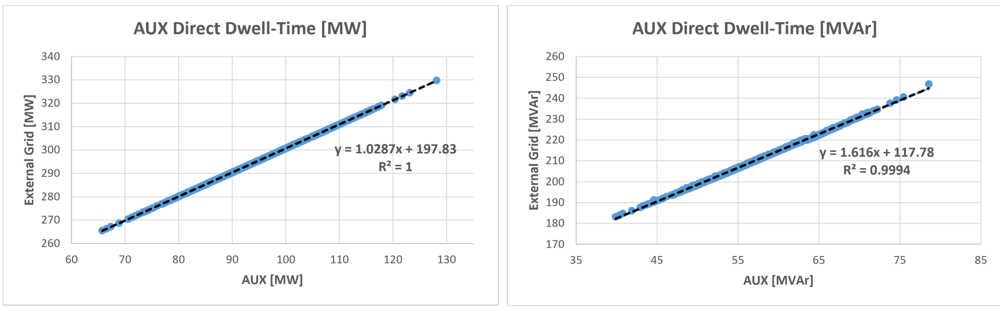
(a)



(b)

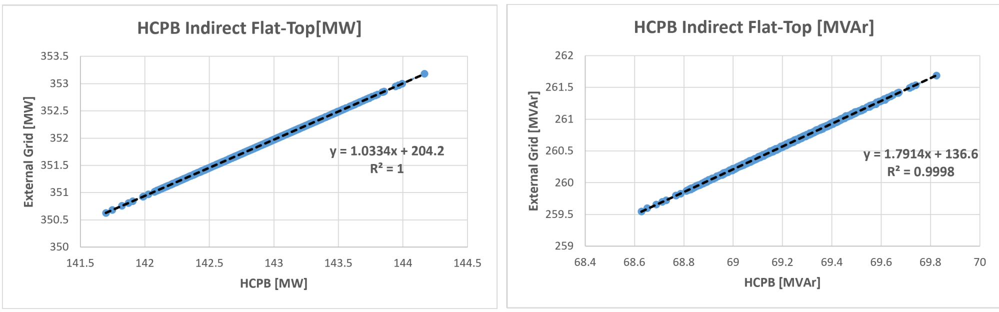


(c)

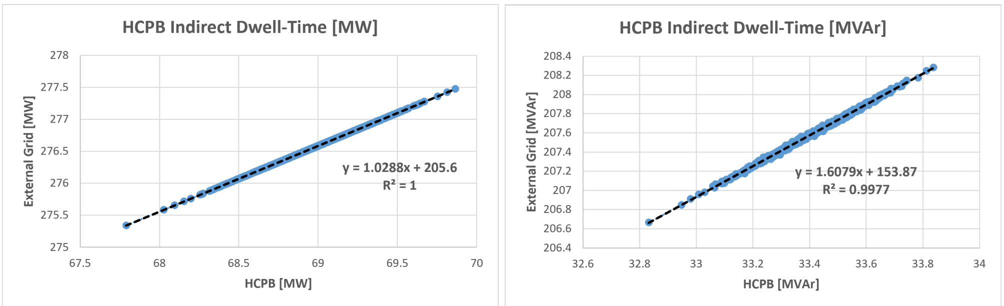


(d)

Figure A.9. Sensitivity analysis and linear regression about the case study of AUX subsystem, considering active power and reactive power both: (a) indirect flat-top, (b) indirect dwell-time, (c) direct flat-top, (d) direct dwell-time.

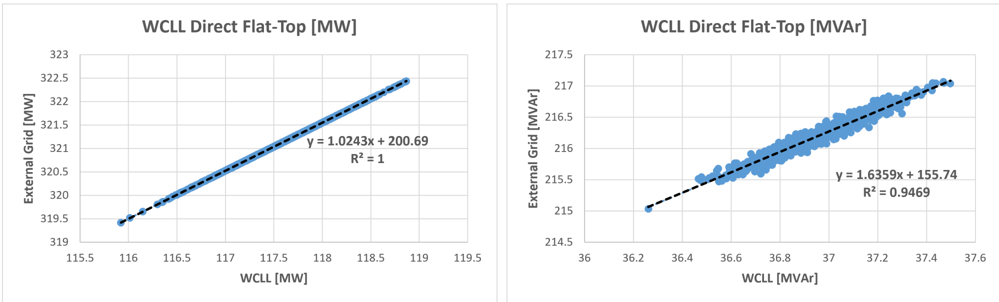


(a)

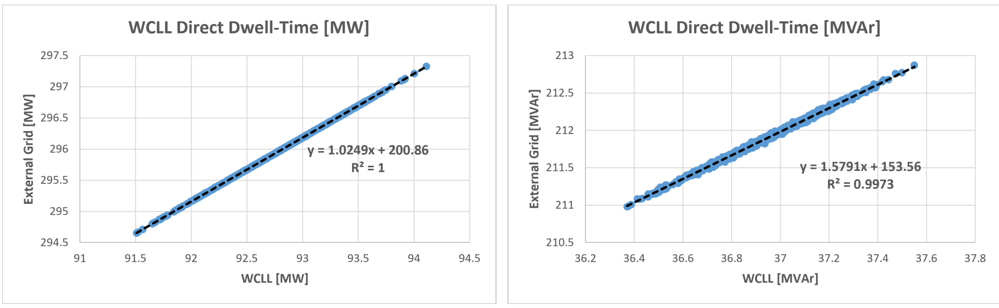


(b)

Figure A.10. Sensitivity analysis and linear regression about the case study of HCPB subsystem, considering active power and reactive power both: (a) indirect flat-top, (b) indirect dwell-time.

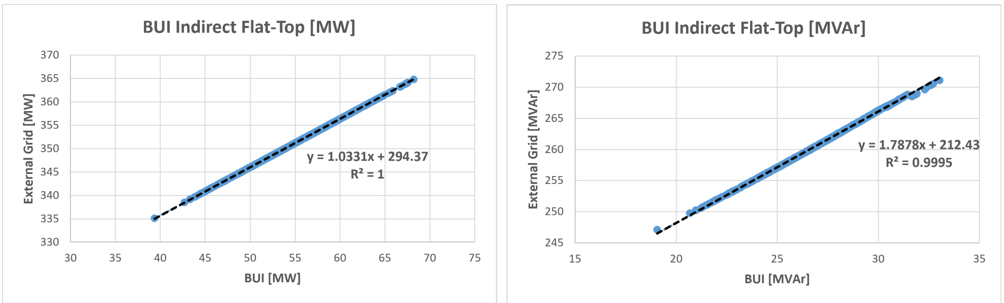


(a)

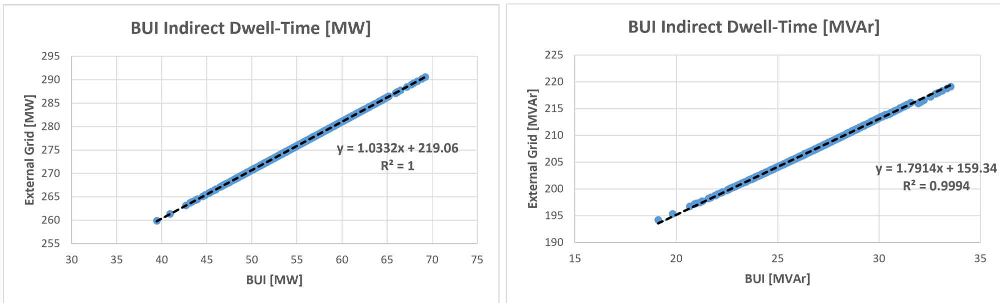


(b)

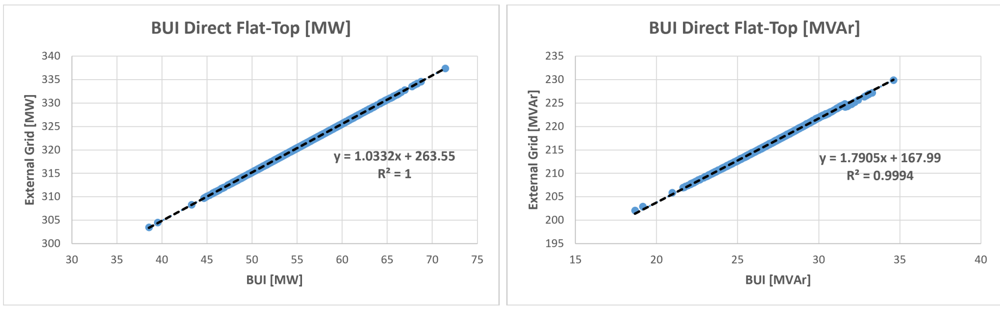
Figure A.11. Sensitivity analysis and linear regression about the case study of WCLL subsystem, considering active power and reactive power both: (a) direct flat-top, (b) direct dwell-time.



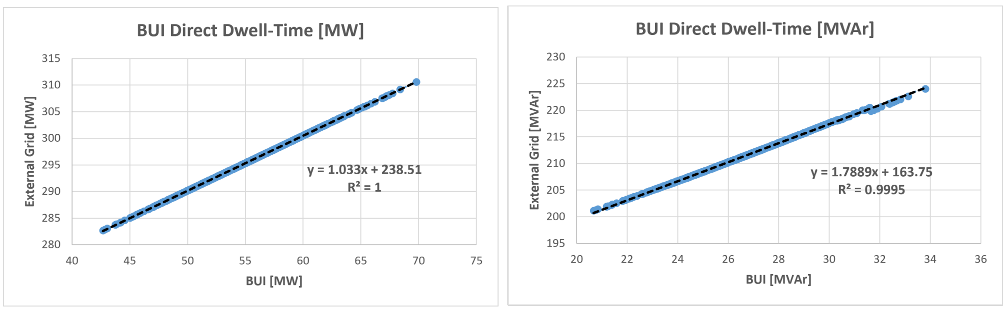
(a)



(b)



(c)



(d)

Figure A.12. Sensitivity analysis and linear regression about the case study of BUI sub-system, considering active power and reactive power both: (a) indirect flat-top, (b) indirect dwell-time, (c) direct flat-top, (d) direct dwell-time.

Bibliography

[1] United Nations Climate Change. Paris agreement. Report, 2015.

[2] Ministero dello Sviluppo Economico. Piano nazionale integrato per l'energia e il clima. Report, Dicember 2019.

[3] Med-TSO. Mediterranean network development plan at 2020.

[4] Terna S.p.A. Piano di sviluppo. Annual report, 2023. https://www.terna.it/it/sistema-elettrico/rete/piano-sviluppo-rete.

[5] Terna S.p.a. Gloassary. https://www.terna.it/en/media/glossary.

[6] Terna S.p.A. Piano di sviluppo. Annual report, 2021. https://www.terna.it/it/sistema-elettrico/rete/piano-sviluppo-rete.

[7] Shafiuzzaman Khan Khadem, Malabika Basu, and Michael Conlon. Power quality in grid connected renewable energy systems: Role of custom power devices. 2010.

[8] M Jawad Ghorbani and Hossein Mokhtari. Impact of harmonics on power quality and losses in power distribution systems. *International Journal of Electrical & Computer Engineering (2088-8708)*, 5(1), 2015.

[9] A Lopez, J Mina, V Cardenas, S De Leon, G Calderon, and J Aguayo Alquicira. Harmonic distortions on grid connected double fed generator: A review. *IEEE Latin America Transactions*, 14(4):1745–1751, 2016.

[10] A Kalair, N Abas, AR Kalair, Z Saleem, and N Khan. Review of harmonic analysis, modeling and mitigation techniques. *Renewable and Sustainable Energy Reviews*, 78:1152–1187, 2017.

[11] Foad H Gandoman, Abdollah Ahmadi, Adel M Sharaf, Pierluigi Siano, Josep Pou, Branislav Hredzak, and Vassilios G Agelidis. Review of facts technologies and applications for power quality in smart grids with renewable energy systems. *Renewable and sustainable energy reviews*, 82:502–514, 2018.

[12] Parlamento Italiano. Attivazione della direttiva 96/92/ce recante norme comuni per il mercato interno dell'energia elettrica, 1999.

[13] European Parliament and the Council. Directive 96/92/ec of the european parliament and of the council of 19 december 1996 concerning common rules for the internal market in electricity, 1996.

[14] European Parliament and the Council. Directive 2003/54/ec of the european parliament and of council of 26 june 2003 concerning common rules for the internal market in electricity and repealing directive 96/92/ec, 2003.

[15] European Parliament and the Council. Directive 2009/72/ec of the european parliament and of the council of 13 july 2009 concerning common rules for the internal market in electricity and repealing directive 2003/54/ec, 2009.

[16] Mauro Caprabianca, Maria Carmen Falvo, Lorenzo Papi, Lucrezia Promutico, Viviana Rossetti, and Federico Quaglia. Replacement reserve for the italian power system and electricity market. *Energies*, 13(11):2916, 2020.

[17] European Parliament and the Council. Commission regulation (eu) 2015/1222, 2015.

[18] GME. Gestore mercati energetici. web site. https://www.mercatoelettrico.org/en/default.aspx.

[19] European Union. Commission regulation (eu) 2017/2195 of 23 november 2017 establishing a guideline on electricity balancing, 2017.

[20] Narayana Prasad Padhy. Unit commitment-a bibliographical survey. *IEEE Transactions on power systems*, 19(2):1196–1205, 2004.

[21] Wim van Ackooij, Irene Danti Lopez, Antonio Frangioni, Fabrizio Lacalandra, and Milad Tahanan. Large-scale unit commitment under uncertainty: an updated literature survey. *Annals of Operations Research*, 271(1):11–85, 2018.

[22] X Bai and H Wei. Semi-definite programming-based method for security-constrained unit commitment with operational and optimal power flow constraints. *IET Generation, Transmission & Distribution*, 3(2):182–197, 2009.

[23] CAISO. Bpm for managing full network model, 2019. http://www.caiso.com/.

[24] Qipeng P Zheng, Jianhui Wang, and Andrew L Liu. Stochastic optimization for unit commitment—a review. *IEEE Transactions on Power Systems*, 30(4):1913–1924, 2014.

[25] Takayuki Shiina and John R Birge. Stochastic unit commitment problem. *International Transactions in Operational Research*, 11(1):19–32, 2004.

[26] Qianfan Wang, Jianhui Wang, and Yongpei Guan. Stochastic unit commitment with uncertain demand response. *IEEE Transactions on power systems*, 28(1):562–563, 2012.

[27] Zhifang Yang, Haiwang Zhong, Qing Xia, and Chongqing Kang. Fundamental review of the opf problem: Challenges, solutions, and state-of-the-art algorithms. *Journal of Energy Engineering*, 144(1):04017075, 2018.

[28] Anya Castillo, Paula Lipka, Jean-Paul Watson, Shmuel S Oren, and Richard P O'Neill. A successive linear programming approach to solving the iv-acopf. *IEEE Transactions on Power Systems*, 31(4):2752–2763, 2015.

[29] Haiti Ma and SM Shahidehpour. Unit commitment with transmission security and voltage constraints. *IEEE transactions on power systems*, 14(2):757–764, 1999.

[30] Anthony Papavasiliou, Shmuel S Oren, and Barry Rountree. Applying high performance computing to transmission-constrained stochastic unit commitment for renewable energy integration. *IEEE Transactions on Power Systems*, 30(3):1109–1120, 2014.

[31] Daniel Bienstock and Apurv Shukla. Variance-aware optimal power flow: Addressing the tradeoff between cost, security, and variability. *IEEE Transactions on Control of Network Systems*, 6(3):1185–1196, 2019.

[32] C Murillo-Sanchez and RJ Thomas. Thermal unit commitment with nonlinear power flow constraints. In *IEEE Power Engineering Society. 1999 Winter Meeting (Cat. No. 99CH36233)*, volume 1, pages 484–489. IEEE, 1999.

[33] Parikshit Pareek and Hung D Nguyen. State-aware stochastic optimal power flow. *Sustainability*, 13(14):7577, 2021.

[34] Steven H Low. Convex relaxation of optimal power flow—part i: Formulations and equivalence. *IEEE Transactions on Control of Network Systems*, 1(1):15–27, 2014.

[35] Na Li, Lijun Chen, and Steven H Low. Exact convex relaxation of opf for radial networks using branch flow model. In *2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm)*, pages 7–12. IEEE, 2012.

[36] Shaojun Huang, Qiuwei Wu, Jianhui Wang, and Haoran Zhao. A sufficient condition on convex relaxation of ac optimal power flow in distribution networks. *IEEE Transactions on Power Systems*, 32(2):1359–1368, 2016.

[37] Idriss Abdou and Mohamed Tkiouat. Unit commitment problem in electrical power system: A literature review. *International Journal of Electrical & Computer Engineering (2088-8708)*, 8(3), 2018.

[38] Marshall L Fisher. The lagrangian relaxation method for solving integer programming problems. *Management science*, 27(1):1–18, 1981.

[39] Florin Capitanescu, JL Martinez Ramos, Patrick Panciatici, Daniel Kirschen, A Marano Marcolini, Ludovic Platbrood, and Louis Wehenkel. State-of-the-art, challenges, and future trends in security constrained optimal power flow. *Electric power systems research*, 81(8):1731–1741, 2011.

[40] Anya Castillo, Carl Laird, César A Silva-Monroy, Jean-Paul Watson, and Richard P O'Neill. The unit commitment problem with ac optimal power flow constraints. *IEEE Transactions on Power Systems*, 31(6):4853–4866, 2016.

[41] Jianfeng Liu, Carl D Laird, Joseph K Scott, Jean-Paul Watson, and Anya Castillo. Global solution strategies for the network-constrained unit commitment

problem with ac transmission constraints. *IEEE Transactions on Power Systems*, 34(2):1139–1150, 2018.

[42] Lei Wu and Mohammad Shahidehpour. Security-constrained unit commitment with uncertainties. *Power grid operation in a market environment: economic efficiency and risk mitigation*, pages 115–168, 2016.

[43] Martin Håberg. Fundamentals and recent developments in stochastic unit commitment. *International Journal of Electrical Power & Energy Systems*, 109:38–48, 2019.

[44] Pavlos Nikolaidis, Anastasios Antoniades, and Sotirios Chatzis. A bayesian optimization approach for the robust unit commitment of identical generating units. 2021.

[45] Chao Ning and Fengqi You. Data-driven adaptive robust unit commitment under wind power uncertainty: A bayesian nonparametric approach. *IEEE Transactions on Power Systems*, 34(3):2409–2418, 2019.

[46] Luigi Acerbi and Wei Ji Ma. Practical bayesian optimization for model fitting with bayesian adaptive direct search. *Advances in neural information processing systems*, 30, 2017.

[47] Hongyu Wu, Mohammad Shahidehpour, Zuyi Li, and Wei Tian. Chance-constrained day-ahead scheduling in stochastic power system operation. *IEEE Transactions on Power Systems*, 29(4):1583–1591, 2014.

[48] Zhi Wu, Pingliang Zeng, Xiao-Ping Zhang, and Qinyong Zhou. A solution to the chance-constrained two-stage stochastic program for unit commitment with wind energy integration. *IEEE Transactions on Power Systems*, 31(6):4185–4196, 2016.

[49] Anthony Papavasiliou and Shmuel S Oren. A comparative study of stochastic unit commitment and security-constrained unit commitment using high performance computing. In *2013 European Control Conference (ECC)*, pages 2507–2512. IEEE, 2013.

[50] Giraldo-Chavarriaga Juan Sebastián, Castrillón-Largo Jhon Alexander, and Granada-Echeverri Mauricio. Stochastic ac optimal power flow considering the probabilistic behavior of the wind, loads and line parameters. *Ingeniería, Investigación y Tecnología*, 15(4):529–538, 2014.

[51] Yi Guo, Kyri Baker, Emiliano Dall'Anese, Zechun Hu, and Tyler Holt Summers. Data-based distributionally robust stochastic optimal power flow—part i: Methodologies. *IEEE Transactions on Power Systems*, 34(2):1483–1492, 2018.

[52] Yi Guo, Kyri Baker, Emiliano Dall'Anese, Zechun Hu, and Tyler Holt Summers. Data-based distributionally robust stochastic optimal power flow—part ii: Case studies. *IEEE Transactions on Power Systems*, 34(2):1493–1503, 2018.

[53] Hossein Sharifzadeh, Nima Amjady, and Hamidreza Zareipour. Multi-period stochastic security-constrained opf considering the uncertainty sources of wind power, load demand and equipment unavailability. *Electric Power Systems Research*, 146:33–42, 2017.

[54] Lucia M Kimball, Kevin A Clements, and Paul W Davis. Stochastic opf via bender's method. In *2001 IEEE Porto Power Tech Proceedings (Cat. No. 01EX502)*, volume 3, pages 4–pp. IEEE, 2001.

[55] U Aytun Ozturk, Mainak Mazumdar, and Bryan A Norman. A solution to the stochastic unit commitment problem using chance constrained programming. *IEEE Transactions on Power Systems*, 19(3):1589–1598, 2004.

[56] Alberto Berizzi, Cristian Bovo, Marco Merlo, Gabriele Callegari, Marco Porcellini, and Massimo Pozzi. Second order sensitivities for constrained reactive optimal power flow. In *2008 43rd International Universities Power Engineering Conference*, pages 1–7. IEEE, 2008.

[57] Yuwei Chen, Ji Xiang, and Yanjun Li. Socp relaxations of optimal power flow problem considering current margins in radial networks. *Energies*, 11(11):3164, 2018.

[58] Abbas Rabiee, Saman Nikkhah, Alireza Soroudi, and Ehsan Hooshmand. Information gap decision theory for voltage stability constrained opf considering the uncertainty of multiple wind farms. *IET Renewable Power Generation*, 11(5):585–592, 2016.

[59] Zhifang Yang, Haiwang Zhong, Qing Xia, Anjan Bose, and Chongqing Kang. Optimal power flow based on successive linear approximation of power flow equations. *IET Generation, Transmission & Distribution*, 10(14):3654–3662, 2016.

[60] Nima Amjady, Shahab Dehghan, Ahmad Attarha, and Antonio J Conejo. Adaptive robust network-constrained ac unit commitment. *IEEE transactions on power systems*, 32(1):672–683, 2016.

[61] Yong Fu and Mohammad Shahidehpour. Fast scuc for large-scale power systems. *IEEE Transactions on Power Systems*, 22(4):2144–2151, 2007.

[62] Ugo Farinelli. Renewable energy policies in italy. *Energy for sustainable development*, 8(1):58–66, 2004.

[63] Patrice Geoffron and Luigi De Paoli. Introduction: a critical overview of the european national energy and climate plans. *Introduction: a critical overview of the European National Energy and Climate Plans*, pages 31–41, 2019.

[64] Keith Williges, Wytze Van der Gaast, Krisztina de Bruyn-Szendrei, Andreas Tuerk, and Gabriel Bachner. The potential for successful climate policy in national energy and climate plans: highlighting key gaps and ways forward. *Sustainable Earth*, 5(1):1–17, 2022.

[65] Angelica Gianfreda, Lucia Parisio, and Matteo Pelagatti. A review of balancing costs in italy before and after res introduction. *Renewable and Sustainable Energy Reviews*, 91:549–563, 2018.

[66] Hannele Holttinen, Peter Meibom, Antje Orths, Bernhard Lange, Mark O'Malley, John Olav Tande, Ana Estanqueiro, Emilio Gomez, Lennart Söder, Goran Strbac, et al. Impacts of large amounts of wind power on design and operation of power systems, results of iea collaboration. *Wind Energy*, 14(2):179–192, 2011.

[67] Fabian Ocker and Karl-Martin Ehrhart. The "german paradox" in the balancing power markets. *Renewable and Sustainable Energy Reviews*, 67:892–898, 2017.

[68] Lion Hirth and Inka Ziegenhagen. Balancing power and variable renewables: Three links. *Renewable and Sustainable Energy Reviews*, 50:1035–1051, 2015.

[69] Simona Bigerna, Carlo Andrea Bollino, Davide Ciferri, and Paolo Polinori. Renewables diffusion and contagion effect in italian regional electricity markets: Assessment and policy implications. *Renewable and Sustainable Energy Reviews*, 68:199–211, 2017.

[70] Simona Bigerna, Carlo Andrea Bollino, and Paolo Polinori. Market power and transmission congestion in the italian electricity market. *The Energy Journal*, 37(2), 2016.

[71] Blanca Moreno, Ana J López, and María Teresa García-Álvarez. The electricity prices in the european union. the role of renewable energies and regulatory electric market reforms. *Energy*, 48(1):307–313, 2012.

[72] Alessandro Sapio. The effects of renewables in space and time: A regime switching model of the italian power price. *Energy Policy*, 85:487–499, 2015.

[73] Iain Staffell. Measuring the progress and impacts of decarbonising british electricity. *Energy policy*, 102:463–475, 2017.

[74] JP Deane, Francesco Gracceva, Alessandro Chiodi, Maurizio Gargiulo, and Brian PO Gallachoir. Assessing power system security. a framework and a multi model approach. *International Journal of Electrical Power & Energy Systems*, 73:283–297, 2015.

[75] DC Sansom, T Downs, and TK Saha. Support vector machine based electricity price forecasting for electricity markets utilising projected assessment of system adequacy data. IPEC, 2003.

[76] EUROfusion. European research roadmap to the realisation of fusion energy, 2018.

[77] ITER. What iter will do. https://www.iter.org/sci/Goals.

[78] ITER. The iter tokamak. https://www.iter.org/mach.

[79] Gianfranco Federici, C Bachmann, L Barucca, Wolfgang Biel, L Boccaccini, R Brown, C Bustreo, S Ciattaglia, F Cismondi, M Coleman, et al. Demo design activity in europe: Progress and updates. *Fusion Engineering and Design*, 136:729–741, 2018.