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Multi-objective optimal power resources planning of microgrids with high penetration of intermittent nature generation and modern storage systems

Sergio Felipe Contreras Paredes

Universidad Nacional de Colombia
School of Engineering, Doctoral program in Electrical Engineering
Bogotá, Colombia

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Sergio Felipe Contreras Paredes

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Advisor:
Camilo Andrés Cortes Guerrero, Ph.D.
Co-Advisor:
Prof.Dr.-Ing. Johanna Myrzik

Research line:
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Research group/institution:
Research group EMC
Universidad Nacional de Colombia
School of engineering, Doctoral program in Electrical Engineering
Bogotá, Colombia

Institute of Automation Techniques - IAT
University of Bremen
Faculty 1 - Physics / Electrical Engineering
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For my parents, sister and life's complice.

"We cannot solve our problems with the same thinking we use when we created them"
Albert Einstein (1879-1955)

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Abstract

Microgrids are self-controlled entities at the distribution voltage level that interconnect distributed energy resources (DERs) with loads and can be operated in either grid-connected or islanded mode. This type of active distribution network has evolved as a powerful concept to guarantee a reliable, efficient and sustainable electricity delivery as part of the power systems of the future. However, benefits of microgrids, such as the ancillary services (AS) provision, are not possible to be properly exploited before traditional planning methodologies are updated. Therefore, in this doctoral thesis, a named Probabilistic Multi-objective Microgrid Planning methodology with two versions, POMMP and POMMP2, is proposed for effective decision-making on the optimal allocation of DERs and topology definition under the paradigm of microgrids with capacity for providing AS to the main power grid.

The methodologies are defined to consider a mixed generation matrix with dispatchable and non-dispatchable technologies, as well as, distributed energy storage systems and both conventional and power-electronic-based operation configurations. The planning methodologies are formulated based on a so-called true-multi-objective optimization problem with a configurable set of three objective functions. Accordingly, the capacity to supply AS is optimally enhanced with the maximization of the available active residual power in grid-connected operation mode; the capital, maintenance, and operation costs of microgrid are minimized, while the revenues from the services provision and participation on liberalized markets are maximized in a cost function; and the active power losses in microgrid´s operation are minimized. Furthermore, a probabilistic technique based on the simulation of parameters from their probabilistic density function and Monte Carlo Simulation is adopted to model the stochastic behavior of the non-dispatchable renewable generation resources and load demand as the main sources of uncertainties in the planning of microgrids. Additionally, POMMP2 methodology particularly enhances the proposal in POMMP by modifying the methodology and optimization model to consider the optimal planning of microgrid's topology with the allocation of DERs simultaneously. In this case, the concept of networked microgrid is contemplated, and a novel holistic approach is proposed to include a multilevel graph-partitioning technique and subsequent iterative heuristic optimization for the optimal formation of clusters in the topology planning and DERs allocation process.

This microgrid planning problem leads to a complex non-convex mixed-integer nonlinear optimization problem with multiple contradictory objective functions, decision variables, and diverse constraint conditions. Accordingly, the optimization problem in the proposed POMMP/POMMP2 methodologies is conceived to be solved using multi-objective population-based metaheuristics, which gives rise to the adaptation and performance assessment of two existing optimization algorithms, the well-known Non-dominated Sorting Genetic Algorithm II (NSGAII) and the Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D). Furthermore, the analytic hierarchy process (AHP) is tested and proposed for the multi-criteria decision-making in the last step of the planning methodologies.

The POMMP and POMMP2 methodologies are tested in a 69-bus and 37-bus medium voltage distribution network, respectively. Results show the benefits of an *a posteriori* decision making with the true-multi-objective approach as well as a time-dependent planning methodology. Furthermore, the results from a more comprehensive planning strategy in POMMP2 revealed the benefits of a holistic planning methodology, where different planning tasks are optimally and simultaneously addressed to offer better planning results.

Keywords: Microgrid, true-Multi-objective optimization, expansion and topology planning, allocation of distributed energy resources, ancillary services, population-based metaheuristic, high-level uncertainties, probabilistic uncertainty modeling, multilevel graph partitioning, multi-criteria decision making.

Resumen

Las microrredes son entes autocontrolados que operan en media o baja tensión, interconectan REDs con las cargas y pueden ser operadas ya sea en modo conectado a la red o modo isla. Este tipo de red activa de distribución ha evolucionado como un concepto poderoso para garantizar un suministro de electricidad fiable, eficiente y sostenible como parte de los sistemas de energía del futuro. Sin embargo, para explotar los beneficios potenciales de las microrredes, tales como la prestación de servicios auxiliares (AS), primero es necesario formular apropiadas metodologías de planificación. En este sentido, en esta tesis doctoral, una metodología probabilística de planificación de microrredes con dos versiones, POMMP y POMMP2, es propuesta para la toma de decisiones efectiva en la asignación óptima de DERs y la definición de la topología de microrredes bajo el paradigma de una microrred con capacidad para proporcionar AS a la red principal.

Las metodologías se definen para considerar una matriz de generación mixta con tecnologías despachables y no despachables, así como sistemas distribuidos para el almacenamiento de energía y la interconnección de recursos con o sin una interfaz basada en dispositivos de electrónica de potencia. Las metodologías de planificación se formulan sobre la base de un problema de optimización multiobjetivo verdadero con un conjunto configurable de tres funciones objetivo. Con estos se pretende optimizar la capacidad de suministro de AS con la maximización de la potencia activa residual disponible en modo conectado a la red; la minimización de los costos de capital, mantenimiento y funcionamiento de la microrred al tiempo que se maximizan los ingresos procedentes de la prestación de servicios y la participación en los mercados liberalizados; y la minimización de las pérdidas de energía activa en el funcionamiento de la microrred. Además, se adopta una técnica probabilística basada en la simulación de parámetros a partir de la función de densidad de probabilidad y el método de Monte Carlo para modelar el comportamiento estocástico de los recursos de generación renovable no despachables. Adicionalmente,la POMMP2 mejora la propuesta de POMMP modificando la metodología y el modelo de optimización para considerar simultáneamente la planificación óptima de la topología de la microrred con la asignación de DERs. Así pues, se considera el concepto de microrredes interconectadas en red y se propone un novedoso enfoque holístico que incluye una técnica de partición de gráficos multinivel y optimización iterativa heurística para la formación óptima de clusters para el planeamiento de la topología y asignación de DERs.

Este problema de planificación de microrredes da lugar a un complejo problema de optimización mixto, no lineal, no convexos y con múltiples funciones objetivo contradictorias,

variables de decisión y diversas condiciones de restricción. Por consiguiente, el problema de optimización en las metodologías POMMP/POMMP2 se concibe para ser resuelto utilizando técnicas multiobjetivo de optimización metaheurísticas basadas en población, lo cual da lugar a la adaptación y evaluación del rendimiento de dos algoritmos de optimización existentes, el conocido *Non-dominated Sorting Genetic Algorithm II* (NSGAII) y el *Evolutionary Algorithm Based on Decomposition* (MOEA/D). Además, se ha probado y propuesto el uso de la técnica de proceso analítico jerárquico (AHP) para la toma de decisiones multicriterio en el último paso de las metodologías de planificación.
Las metodologías POMMP/POMMP2 son probadas en una red de distribución de media tensión de 69 y 37 buses, respectivamente. Los resultados muestran los beneficios de la toma de decisiones *a posteriori* con el enfoque de optimización multiobjetivo verdadero, así como una metodología de planificación dependiente del tiempo. Además, los resultados de la estrategia de planificación con POMMP2 revelan los beneficios de una metodología de planificación holística, en la que las diferentes tareas de planificación se abordan de manera óptima y simultánea para ofrecer mejores resultados de planificación.

Palabras clave: Microrred, optimización multi-objetivo verdadera, planeamiento, asignación de recursos de energía distribuidos, serviciós auxiliares, metaheuristicas basadas en poblaciones, incertidumbres de alto nivel, modelo probabilistico de incertidumbres, partición de grafos multinivel, toma de decisión multicriterio.

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List of symbols and abbreviations

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Symbols

Symbol	Term	Unit SI
Subscripts and Superscripts		
mt	Microturbines	
wt	Wind turbines	
pv	Photovoltaic units	
ba	Battery units	
c	Generation technologies with continuous variables	
g	Discrete generation technologies	
j	Set of technologies ($g \cup c$)	
b	Set of storage technologies	
i	Set of technologies ($j \cup b$)	
l	Load	
bus	Bus	
br	Branch (lines)	
clu	Cluster	
mg	Microgrid	
λ	Loop (cycle) in the network	
m	Month 1, 2, ..., 12	
d	Day type: weekday, weekend peal day	
h	Hour 1, 2, ..., 24	
$t(m, d, h)$	Time segment along the horizon planning	
d	Decision variable (in the optimization problem)	
ic	Inequality constraint	
ec	Equality constraint	
Optimization problem		

Symbol	Term	Unit SI
$\vec{x}$	Variables vector	
$\vec{z}$	Objective functions vector $\vec{F}(\vec{x})$	
S	Feasible decision variables space	
Z	Feasible objective space	
f_1	Objective functions 1 in POMMP and POMMP2	
f_2	Objective functions 2 in POMMP and POMMP2	
f_3	Objective functions 3 in POMMP and POMMP2	
f_{k1}	Penalized objective functions 1 in POMMP2	
f_{k2}	Penalized objective functions 2 in POMMP2	
f_{k3}	Penalized objective functions 3 in POMMP2	
g_{ic}	Inequality constraint function	
g_{ec}	Equality constraint function	
M	Arbitrarily large number	$[-]$
$\mathrm{m} = 3$	Number of objective functions	
$\mathrm{N_d}$	Number of decision variables (also called n)	
$\mathrm{N_{ic}}$	Number of inequality constraints	
$\mathrm{N_{ec}}$	Number of equality constraints	
$\mathrm{N_{pop}}$	Population size	
$\mathrm{N_{gen}}$	Generations size	
$\boldsymbol{\lambda}$	Coefficient weight vector in MOEA/D	
T	Neighborhood size in MOEA/D	

Multi-criteria decision making

Symbol	Term	Unit SI
B	Comparison matrix of the AHP	
b	Weights for each pair of criteria or alternatives based on Saaty's scale in the AHP	
λ_{max}	Maximum eigenvalue of the matrix B in the AHP	
CI	Consistency index in the AHP	
CR	Consistency ratio in the AHP	
$\mathbb{RI}$	Saaty's index for the CR evaluation	
α	Required consistency level	
W	Normalized relative relevance among criteria or alternatives in the AHP	
$\vec{\mathrm{W}}_{\mathrm{F}}$	Normalized weights vector of the criteria in the AHP	
$\vec{\mathrm{W}}_{\mathrm{S}}$	Normalized weights vector of the alternatives in the AHP	
$\vec{\mathrm{R}}_{\mathrm{p}}$	Ranking vector of the solutions in the AHP	

Graph partitioning and topology

Symbol	Term	Unit SI
$\mathrm{G_o}$	Original networked microgrid graph	

Symbol	Term	Unit SI
G_{i}	Initial networked microgrid graph	
G_{r}	Reduced networked microgrid graph	
V	Vertices (buses) of the networked MG	
E	Edges (lines) of the networked MG	
k	Subset of vertices $k \in V$	
Λ	Loop (cycle) in the network	
Clu_o	Cluster candidates	
Clu_r	Cluster refined selected	
Clu_s	Cluster selected	
P_k	Set of k sub-sets of V and partition of G	
n_{clu}	Number of clusters in the microgrid	
n_λ	Number of loops per each cluster	
Electrical data		
$\mathbf{I}$	Complex current	[A]
$\mathbf{V}$	Complex bus bar voltage	[V]
$\mathbf{Z}$	Impedance	[Ω]
R	Resistance	[Ω]
X	Reactance	[Ω]
L	Inductance	[H]
$\mathbf{S}$	Complex power	[kVA]
P_{DG}	Active power generated	[kW]
P_{DS}	Power of storage systems	[kW]
$\mathrm{P}_{\mathrm{load}}$	Power demanded	[kW]
$\mathrm{P}_{\mathrm{loss}}$	Power losses	[kW]
$\mathrm{P}_{\mathrm{fed}}$	Active power at the feeder	[kW]
$\mathrm{P}_{\mathrm{lshed}}$	Active power demanded after load shedding	[kW]
$\mathrm{PI}_{\mathrm{DG}}$	Active power generated in islanded mode	[kW]
$\mathrm{PI}_{\mathrm{DS}}$	Power of storage systems in islanded mode	[kW]
$\mathrm{PI}_{\mathrm{load}}$	Power demanded in islanded mode	[kW]
$\mathrm{PI}_{\mathrm{loss}}$	Power losses in islanded mode	[kW]
PI_{lshed}	Power of critical loads	[kW]
Q_{DG}	Reactive power generated	[kVAr]
$\mathrm{Q}_{\mathrm{load}}$	Reactive power demanded	[kVAr]
$\mathrm{Q}_{\mathrm{fed}}$	Reactive power at the feeder	[kVAr]
$\mathrm{Q}_{\mathrm{lshed}}$	Reactive power demanded after load shedding	[kVAr]
General system parameters		
N_{mt}	Total number of microturbine units	

Symbol	Term	Unit SI
N_{wt}	Total number of wind turbine units	
N_{pv}	Total number of photovoltaic systems	
N_{ba}	Total number of battery systems	
N_{bus}	Total number of buses in the grid	
N_{br}	Total number of branches	
N_{t}	Total number of time-segments	
l_{shed}	Set of loads disconnected after shedding	
I_{G_g}	Number of units of generation technology g installed	[−]
L	Length of the lines	[km]
N_{clu}	Maximum number of clusters	
N_{λ}	Maximum number of loops; $mg = clu$ per cluster	
$\min\|k_{\lambda}\|$	Minimum number of buses per loop	
V_{max}	Maximum voltage limit in buses	[V]
V_{min}	Minimum voltage limit in buses	[V]
S_{MinBid}	Minimum bid for spinning reserve provision	[kW]
NS_{MinBid}	Minimum bid for non-spinning reserve provision	[kW]
$R_{UpMinBid}$	Minimum bid for frequency up-regulation provision	[kW]
$R_{DnMinBid}$	Minimum bid for frequency down-regulation provision	[kW]
θ	Auxiliary service supplying time	[h]
System operation		
U_{L}	Energy purchased	[kW]
G_{T}	Total power generated	[kW]
P_{g}	Active power generated by the technology g	[kW]
H_{g}	Number of hours that the technology g can operate	[h]
G_{S}	Power generated to be exported	[kW]
T_{oPG}	Total active power generated	[kW]
P_{Aexp}	Total active power exported	[kW]
P_{Aixp}	Total active power imported	[kW]
T_{oPD}	Total active power demanded	[kW]
P_{loss}	Total active power lost	[kW]
T_{oPGI}	Total active power generated in islanded mode	[kW]
T_{oPDI}	Total active power demanded in islanded mode	[kW]
P_{lossI}	Total active power lost in islanded mode	[kW]
S_{Out}	Output power in the storage system	[kWh]
S_{OutS}	Output power in the storage systems for spinning reserve provision	[kWh]
S_{OutNS}	Output power in the storage systems for non-spinning reserve provision	[kWh]

Symbol	Term	Unit SI
S_{OutMR}	Output power in the storage systems for internal consumption of the mcirogrid	[kWh]
S_{OutRUP}	Output power in the storage systems for frequency down-regulation provision	[kWh]
S_{In}	Input power in the storage systems	[kWh]
S_{InMR}	Input power in the storage systems for internal consumption of the microgrid	[kWh]
S_{InRDn}	Input power in the storage systems for frequency down-regulation	[kWh]
S	Total active power generated for spinning reserve export	[kW]
NS	Total active power generated for non-spinning reserve export	[kW]
R_{Up}	Total active power generated for frequency up-regulation export	[kW]
R_{Dn}	Total active power generated for frequency down-regulation export	[kW]
b_{ps}	Binary decision of selling or purchasing electricity to the main grid	[b]
b_{Aux}	Binary decision of supplying AS	[b]
b_{TEx}	Binary decision of selling electricity to the stock	[b]
b_{S}	Binary decision of selling spinning reserve	[b]
b_{NS}	Binary decision of selling non-spinning reserve	[b]
b_{RUp}	Binary decision of selling frequency up-regulation	[b]
b_{RDn}	Binary decision of selling frequency down-regulation	[b]
b_{Bpk}	Binary decision of charge/discharge based on power peak	[b]
Market data		
T_{F}	Regulated tariff fixed charge for electricity in month m	[$]
T_{E}	Regulated tariff for electricity	[$/kWh]
T_{arMAX}	Maximum rate between different services to export to the grid	[$]
T_{Ex}	Regulated tariff for electricity export	[$/kWh]
S_{MCP}	Regulated tariff for spinning reserve export	[$/kWh]
NS_{MCP}	Regulated tariff for non-spinning reserve export	[$/kWh]
R_{UpMCP}	Regulated tariff for frequency up-regulation export	[$/kWh]
R_{DnMCP}	Regulated tariff for frequency down-regulation export	[$/kWh]
Technology data		
Cap	Rated power capacity of generation	[kW]

Symbol	Term	Unit SI
C_{VC}	Generation cost	[$/kWh]
C_{OMV}	Variable annual operation and maintenance costs	[$/kWh]
C_{CCD}	Turnkey capital cost of generation	[$/kW]
C_{OMF}	Fixed annual operation and maintenance costs	[$/kW]
C_{FCC}	Fixed capital cost of generation	[$/kW]
C_{CCB}	Turnkey capital cost of lines installation	[$/km]
L_t	Expected lifetime of technology	[years]
A_U	Used physical area of technology	[m^2]
A_{Disp}	Available physical area at the buses for technology installation	[m^2]
Investment parameters		
I_R	Interest rate	[%]
An_c	Annuity factor for investments in technologies c	[−]
An_g	Annuity factor for investments in technologies g	[−]
An_b	Annuity factor for investments in technologies b	[−]
An_{br}	Annuity factor for investments in technologies br	[−]
Microturbines		
α	Power angle	[$\circ$]
$\mathbf{E}$	Internal voltage synchronous generator	[V]
Wind turbines data		
A	Area of the drown circle by the blades' tip	[m^2]
ρ	Density of the air mass	[kg/m^3]
P_0	Power contained in the air	[kW]
P_T	Power absorbed by the wind turbine	[kW]
P_{wt}	Output power of the wind turbine	[kW]
Pr_{wt}	Rated Power in the wind turbine	[kW]
v	Wind speed	[m/s]
v_i	Cut-in wind speed	[m/s]
v_r	Rated wind speed	[m/s]
v_o	Cut-out wind speed	[m/s]
c_p	Power coefficient	[%]
N	Revolutions per minute of the rotor blades	[min^{-1}]
D	Diameter of the circle described by the tips of the blades	[m]
Photovoltaic systems		
E	Solar irradiance	[W/m^2]

Symbol	Term	Unit SI
E_g	Global solar irradiance	[W/m^2]
E_stc	Solar irradiance for the STC	[W/m^2]
$\mathrm{P_{MPP}}$	Maximum power point	[W]
$\mathrm{I_{MPP}}$	Current at maximum power point	[A]
$\mathrm{I_{sc}}$	Short circuit current	[A]
$\mathrm{V_{MPP}}$	Voltage at maximum power point	[V]
$\mathrm{V_{oc}}$	Open circuit voltage	[V]
$\mathrm{P_{pv}}$	Output power of the PV system	[W]
$\mathrm{Pr_{pv}}$	Rated Power of the PV system	[$\mathrm{W_p}$]
$\mathrm{A_{Module}}$	Area of a single PV module	[m^2]
η_sys	PV system efficiency	[%]
η_rated	PV rated efficiency	[%]
$\eta_\mathrm{inverters}$	Losses in the inverters	[%]
$\eta_\mathrm{reflection}$	Losses due to reflections	[%]
$\eta_\mathrm{connection}$	Losses of the connections	[%]
$\eta_\mathrm{temperature}$	Temperature effect	[%]
η_shading	Shadows and irregularities effect	[%]
$\mathrm{f_{inclined}}$	Gains and losses due to modules inclination and orientation	[%]
ϑ	Modules temperature	[°C
AM	Solar spectrum	[–]
$\mathrm{R_c}$	Solar irradiation at certain radiation point	[W/m^2]
Battery systems		
$\mathrm{C_{ba}}$	Battery capacity	[Wh]
SOC	State of charge of the storage system	[Wh]
DOC	Deep of charge of the storage system	[Wh]
MOC	Maximum of charge of the battery	[Wh]
DOD	Maximum deep of discharge of the battery	[Wh]
$\mathrm{E_{ch}}$	Incoming energy to the storage system	[kWh]
$\mathrm{E_{dch}}$	Outgoing energy from the storage system	[kWh]
$\mathrm{E_{ba}}$	Available battery energy	[kWh]
$\mathrm{P_{ba}^{ch}}$	Input power of the battery system	[W]
$\mathrm{P_{ba}^{dch}}$	Output power of the battery system	[W]
$\mathrm{V_{ch}}$	Voltage during the charging cycle	[V]
$\mathrm{V_{dch}}$	Voltage during the discharging cycle	[V]
$\mathrm{I_{ch}}$	Current during the charging cycle	[A]
$\mathrm{I_{dch}}$	Curret during the discharging cycle	[A]
$\Delta\mathrm{t_{ch}}$	Charging cycle duration	[h]
$\Delta\mathrm{t_{dch}}$	Discharging cycle duration	[h]

Symbol	Term	Unit SI
η_{E}	Energy efficiency in the ESS	[%]
η_{ba}	Self discharge coefficient	[%]
η_{ch}	Battery's charging efficiency	[%]
η_{dch}	Battery's discharging efficiency	[%]
b_{ch}	Binary decision of charging operation	[b]
$\mathrm{b}_{\mathrm{dch}}$	Binary decision of discharging operation	[b]

Probability density functions - PDF

k	Shape parameter of the Weibull distribution	
λ	Scale parameter of the Weibull distribution	
μ	Mean value (of logarithmic values for the log-normal distribution)	
σ	Standard deviation (of logarithmic values for the log-normal distribution)	
B	Beta function	
α	Shape parameter of the Beta distribution	
β	Shape parameter of the Beta distribution	

Abbreviations

Abbreviation	Definition
AC	Alternating Current
ADN	Active Distribution Network
AENS	Energy Not Supplied for Average Case
AHP	Analytic Hierarchy Process
AM	Active Management
AMS	Active Management System
ANSI	American National Standards Institute
AS	Ancillary Service
BA	Battery
BC	Britich Columbia
BM	Biomass Generation
CAISO	California Independent System Operator
CC	Microgrid Central Control
CES	Community Energy Storage
CERTS	Consortium for Electric Reliability Technology Solutions
CHP	Combined Heat and Power
CIGRE	International Council on Large Electric Systems
CLLI	Overall Contingency Load Loss Index
CM	Capacity Market Programs
CPP	Critical Peak Pricing
DS	Distributed Storage
DSO	Distribution Energy Operation
DNO	Distribution Network Operation
DER	Distributed Energy Resources
DC	Direct Current
DFIG	Doubly-fed Induction Generator
DG	Distributed Generation
DGENCO	Distributed Generation Company
DLC	Directly Controllable Loads
DISCO	Distribution Company
EDRP	Energency Demand Response Program
EPS	Energy Power System
EM	Energy Management
EMM	Energy Management Module
ENS	Energy Not Supplied
EENS	Expected Energy Not Supplied
ESS	Energy Storage System

Abbreviation	**Definition**
EU	European Union
FC	Fuel Cell
GENCO	Generation Company
HAM	Hybrid Agent Model
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
I/C	Interruptible / Curtailable rates
ICE	Internal Combustion Engine
IG	Induction Generator
Inv	Inverter
IPP	Independent Power Producer
IDSO	Independent Distribution System Operator
ISO	Independent System Operator
MCS	Monte Carlo Simulation
MC	Microgrid DERs Controllers
MPP	Maximum Power Point
MT	Microturbine
MOEA/D	Multi-objective Evolutionary Algorithm Based on Descomposition
NEC	National Electric Code
NDE	Non-Delivered Energy
NSGAII	Non-dominated Sorting Genetic Algorithm
PHEV	Plug-in hybrid electric vehicle
PCC	Point of Common Coupling
PV	Photovoltaic units
POMMP	Probabilistic Multi-objective Microgrids Planning
POMMP2	Probabilistic Multi-objective Microgrids Planning 2
PDF	Probabilistic Density Function
PQR	Power Quality and Reliability
PR	Performance Ratio of the PV systems
RDSI	Renewable and Distributed Systems Integration
RTO	Regional Transmission Organization
RTP	Real Time Pricing
RSO	Regional System Operator
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SAIUI	System Average Interruption Unavailability Index
SG	Synchronous generator
SSW	Section Switch
STC	Standard Test Conditions

Abbreviation	Definition
TOU	Time of Use
TSO	Transmission System Operator
TSR	Tip Speed Ratio
TSW	Tie Switch
UL	Underwriters Laboratory
USA	The United States of America
VOLL	Value of Lost Load
WD	Typical Weekday
WE	Typical Weekend day
WT	Wind Turbine

1. Introduction

The electric power sector is currently facing one of the most remarkable transformations in their operational and structural paradigms since its earliest large-scale industrialization. Worldwide policies regarding energy transition usage and reduction of CO_2 emissions have given rise to powerful concepts such as **microgrids**, which has emerged to enable a massive deployment of distributed energy resources (DERs) strongly have characterized by variable and sometimes hardly predictable generation matrix mainly powered by renewable energies. This ongoing phenomenon requires academics, engineers, and electric power industry-leaders to radically reconsider the strategies on how power systems, and more specifically microgrids, are operated and conceived from planning. Hence, in this dissertation, a named probabilistic multi-objective microgrids planning methodology with two versions, POMMP and POMMP2, is proposed to tackle the challenges of managing an optimal decision making for the allocation of DERs and microgrid's topology definition in a holistic way and under the framework of a microgrid with capacity for providing ancillary services.
As part of the introduction, Section 1.1 presents the context of the current power systems and microgrids. Afterward, Section 1.2 describes the main motivation for this doctoral research, while the research objectives and questions are described in Section 1.3. Section 1.4 discloses the main contributions and highlights of the research and the publications that compose the current dissertation and were part of the doctoral research execution are listed. To end the introductory chapter, the outline of the remainder of this dissertation is presented in the 1.5.

1.1. Context

Electricity has unquestionably become one of the main pillars of modern society, and with this, electrical engineers, researchers, stakeholders, and population, in general, have witnessed a steadily increasing demand for the electrical energy supply. This result is not unexpected since the level of success of a country's economy has depended for decades on its ability to produce and provide goods and services, which is directly linked with the electricity provision. However, it has been also clear that energy use has lead to increasing costs and environmental repercussions related to burning fossil fuels. For example, the transport sector represents almost a quarter of Europe's greenhouse gas emissions, and the electric power industry is currently responsible for 30-40% of the greenhouse gas emissions in industrialized countries, and almost around 60% of total global greenhouse gas emissions (Hohmeyer and Bohm, 2015; United Nations, 2020). These facts have motivated local national and international policy-makers to guarantee affordable, secure, reliable, efficient, and sustainable electricity supplying through investments in renewable energy resources, improvements in energy-efficient practices, and the implementation of clean energy infrastructure and technologies. These requirements have impacted the regular power industry's duties and led to search urgent solutions for massive integration of renewable generation resources, energy storage systems (ESS), power electronic technologies (e.g. converters), a sustainable and optimal grid expansion, the support to electro-mobility technologies and load profiles changes. Therefore, utilities must find solutions to manage demand and guarantee secure, reliable, efficient, and sustainable electricity supply. Hence, integration of renewable resources and decentralization of the mainstream power system are nowadays some of the most representative challenges for power and energy engineers, researchers, and stakeholders (Farhangi and Joos, 2019; Chowdhury *et al.*, 2009).

Historically, the first electric power systems were introduced as small direct current (DC) systems for most industrial purposes, where the generation had to remain close to the loads. The first electric power system was settled in 1882 by Thomas Edison in the United States, but the DC systems limitations at that time and the invention of the transformer (1885) and the induction motor (1888), gave rise to alternating current (AC) power systems (Jayaweera, 2016). The first single-phase AC line was put into operation in 1889 in the United States, while the first three-phase line came into operation in Germany (1891) with 179km length and a voltage level of 12kV (Glover and Sarma, 2003). In this context, the electrical industry grew from the beginning in 1882 until 1972 with a considerable rhythm based on continuous expansion, price reduction, novel technological achievements, and visionary engineering (Glover and Sarma, 2003).

Electric power systems have kept since then a strictly hierarchical structure, where power plants are at the top and loads are at the bottom of the power flow chain under a so called passive operation. The power industry has worked with a defined separation among generation, transmission, and distribution subsystems to carry electricity from power plants to customers, which can be concentrated in cities and villages or isolated in remote places. This conventional concept for the power systems was developed to fulfill the demand requirements during most of the last century. However, a lack of sustainability in the use of natural resources for electricity generation, the environmental footprint due to fossil fuels-based generation and the constant increase of the demand, reliability, and efficiency in the electricity provision have led to extensive research to tackle the challenges of the power systems of the future (Chowdhury *et al.*, 2009, Chapter 1).

These problems have given rise to a growing worldwide trend of generating power closer to the demand (locally) and at distribution voltage levels (Chowdhury *et al.*, 2009, Chapter 1). Some motivations have been the prominent increase in the apprehension regarding the impacts of the electric power industry to climate change since earliest 2000s, and with this, the penetration level of renewable generation technologies; benefits in terms of efficiency due to possibilities such as the re-use of conventionally wasted heat; open opportunities to implement novel energy storage technologies at the low voltage (LV) and medium voltage (MV) levels; and flexibility in the system operation because of the active participation of the demand side in the power generation (Jayaweera, 2016).

The type of non-conventional and/or renewable sources that are located close to the end-users and comprise smaller capacities compared with conventional centralized generators are defined as distributed generators (DGs). Some DGs technologies are micro-turbines, Stirling engine generators, combined heat and power (CHP) systems, fuel cells, etc., which at the same time are propelled from different types of primary energies such as natural gas, biogas, biomass, diesel, etc. On the other hand, the most common and extended used renewable technologies are solar photovoltaic cells (PV), wind power, and small micro hydropower plants (Chowdhury *et al.*, 2009, Chapter 1).

Furthermore, one of the most critical issues has been the technical difficulties and involved high costs of storing electrical energy and for the used in the future. However, the development of mobile devices and technologies, electrical vehicles (EVs), and the increasing integration of non-dispatchable DG technologies as PV and wind turbines (WT) have accelerated the research, ongoing advances and cost reduction in technologies for energy storage systems (ESS). Some examples of technologies are the one based on chemical energy storage such as batteries, kinetic energy storage such as flywheels (storage of rotating kinetic energy), static energy storage with the super-capacitors, potential energy storage employing, for instance, the use of the gravitational potential energy and the transportation of high masses of water at higher relative altitudes, and pressure energy storage with the compression of air in underground reservoirs (Tan *et al.*, 2013). However, ESSs such as batteries have attracted special attention due to their flexibility to be installed close to demand centers and their pronounced reduction in manufacturing costs.

The whole group of DG, distributed ESS are also called distributed storage (DS), and demand management systems are called a DERs (Lasseter *et al.*, 2002). In the last decades, the integration of the DERs into the traditional passive distribution networks, which involves a centralized generation and unidirectional electricity transportation, has led to the major transition era into a decentralized generation, bi-directional electricity transportation and the active participation of the demand side, which gives rise to the concept of Active Distribution Network (ADN) (CIGRE WG C6.11, 2009; Chowdhury *et al.*, 2009, Chapter 1). ADN are defined by CIGRE WG C6.11 (2009) as distribution networks that have systems able to control a combination of DERs (generators, loads and storage), while the distributed system operators (DSOs) have the capacity of managing the electricity flows supported on flexible network topology and DERs assumes some degree of responsibility for system support depending on appropriate regulation conditions and connection agreements.

Some authors claim that we are experimenting the era of major transition from traditional passive distribution networks with unidirectional electricity transportation into active distribution networks (ADN) with bi-directional electricity transportation (Chowdhury *et al.*, 2009, Chapter 1), which have brought about engineering challenges with high levels of com-

plexity. In general, the integration and interconnection of different technologies of DERs (generators, loads, and storage) that operate under a combination of central and distributed controlled systems have given rise to hybrid power energy systems, which currently comprises power-electronic-based, AC-DC and multimodal architectures (CIGRE WG C6.11, 2009; Chowdhury *et al.*, 2009). Furthermore, the decentralization of the power generation with penetration of both dispatchable and non-dispatchable technologies as well as the possibility of implementing self-controllable entities as part of the power networks have brought about the proposal of envisioning new self-controlled entities as part of the power grids.
That is the case of the microgrid concept, which was conceptually considered for the first time during the earliest 2000 by Lasseter (2001) and Marnay *et al.* (2001). In general, microgrids can be defined as self-controlled entities that can operate in either grid-connected or islanded modes at medium or low voltage level by means of the coordinated management of interconnected DERs and different load (Contreras *et al.*, 2019; CIGRE WG C6.22, 2015a). The microgrid concept has been presented as a powerful approach to boost the current transition from passive to active distribution networks, to manage the high penetration of DERs, to facilitate effective local control strategies, and to satisfy the requirement of highly reliable, stable, secure, efficient and sustainable electricity delivery. The characteristics of the microgrids are explained in detail in Chapter 2 of this dissertation. Research on microgrids has considerably increased in the last decade, and in this context, Farhangi and Joos (2019) claim that research work in this area could follow the three themes below:

- Theme 1: Operation, control, and protection of microgrids
- Theme 2: Microgrid planning, optimization, and regulatory issues
- Theme 3: Microgrid communication and information technologies

The microgrid concept has evolved in different directions, and despite its characteristics have been extensively presented and explained, these can variate among authors' definitions (CIGRE WG C6.22, 2015a; Lasseter *et al.*, 2002). Therefore, the concept has sometimes been used without a proper consideration of its classification (Martin-Martínez *et al.*, 2016), and sometimes confused with other definitions such as ADNs (CIGRE WG C6.19, 2014), hybrid AC-DC distribution networks (He *et al.*, 2019), multi-energy systems (Mancarella, 2014) or Smart Power Cells (Mayorga Gonzalez *et al.*, 2020). Consequently, different studies have tried to characterize and propose a proper classification for different types of microgrids depending on their characteristics, voltages levels, operators, and owners. Thus, CIGRE WG C6.22 (2015a) proposes four types of microgrids: Customer microgrids or true microgrids, utility microgrid or milligrid, remote microgrid or not true microgrid and virtual microgrid. Furthermore, other classifications or composed concepts have arisen, for example, networked microgrids (Alam *et al.*, 2019) or nanogrids (Martin-Martínez *et al.*, 2016). This classification and context are expanded in Chapter 2 of this dissertation.

1.2. Motivation

In general, microgrid's operation, control, protection, and planning strategies have been studied widely. Initially, operation and control issues were studied deeper compared with research regarding the microgrid planning problem, since academics and stakeholders focused on the feasibility issues and benefits exploitation of the new concept (Hirsch *et al.*, 2018; Lede *et al.*, 2017; Parhizi *et al.*, 2015; Ustun *et al.*, 2011; Jiayi *et al.*, 2008). However, research on the planning problem has steadily increased and gotten special attention, which is an extremely necessary and sensible task, since optimal decision making in the planning stage is essential for satisfying growing demand and requirements in a cost-effective, reliable and secure manner.

In the planning problem, it is evident that the main focus and challenges for planning the future power systems will move toward the planning of modern ADN with concepts such as microgrids. Therefore, it is clear that planning at the distribution level cannot be addressed anymore with traditional methodologies, where the distribution systems are planned based mainly on networks that interconnect load centers/points and there is an unidirectional power flow from the main transmission and distribution grid into the MV and LV networks, respectively (Seifi and Sepasian, 2011).

Traditional distribution network planning and expansion methodologies have focused normally on the grid reconfiguration, construction of new lines, installation of new transformers, and also the allocation of reactive power resources. Furthermore, it has been based on deterministic methods and the strategy of "fit and forget", as well as worst-case profiles and low-probability scenarios (Xiang *et al.*, 2016; Li *et al.*, 2017). Notwithstanding, the massive integration of DERs and the proposal of new market concepts have considerably changed the principles of distribution system planning (Ghadi *et al.*, 2019), and the deficiencies of the traditional methods have been increasingly becoming evident and problematic. For example, they have been responsible for worthless distribution network reinforcements, increasing network losses, and unreachable development and environmental targets, which make them no longer valid for the ADN and microgrid planning (Li *et al.*, 2017).

The microgrid planning is a complex and extensive task that has been researched from different perspectives as it can be found in extensive review papers for the planning of ADNs (Ghadi *et al.*, 2019; Lakshmi and Ganguly, 2018; Li *et al.*, 2017; Xiang *et al.*, 2016; Martin-Martínez *et al.*, 2016; Georgilakis and Hatziargyriou, 2015; Keane *et al.*, 2013; Alarcon-Rodriguez *et al.*, 2010). Reviews are given about particular theoretical issues, challenges, requirements, and conditions for the planning of ADNs. A deeper analysis to their outcomes brings to the conclusion that although planning issues have been fairly studied separately, new planning methods have been apprehensively proposed. For example, new methodologies have evolved maintaining prudent similarities with well-known conventional planning strategies, focused on tackling individual requirements, and including progressively, although disjointedly, new key features as in Table **1-1** (Ghadi *et al.*, 2019; Li *et al.*, 2017). These individual approaches may be understood due to the lack of worldwide general agreements to define and characterize emerging power distribution network architectures, which at the same time is partially an effect of the strong case-dependency of the practical integration of DERs and current regulatory barriers. Some of the key features for the microgrid planning are shown in Table **1-1**.

One of the main challenges to tackle the microgrid planning problem is the high variability and the strong case-dependency of the microgrid's key characteristics that must be considered from the planning stage. Furthermore, this issue is even more complex due to the lack of consensus in the definition and understanding of the microgrid's concept scope as well as the rich diversity of paradigms for the microgrid planning.

In every case, the planning of microgrids can be defined as a process that aims to decide on new or upgrading elements of the network to adequately satisfy an expected future load demand (Seifi and Sepasian, 2011). These types of decision makings require the solution of an optimization problem, which consists of the definition, modeling, and solution steps. The definition of the optimization problem comprises a convenient selection of dependent and independent decision variables, objective functions, and constraint functions (Seifi and Sepasian, 2011). Afterward and before any optimization can be done, the decision-maker should model the optimization problem in an appropriate form to be solved (Branke *et al.*, 2008). The mathematical or computation model for accomplishing the microgrid's planning optimization problem is a complex, critical and important step that depend significantly on the microgrid's planning requirements and actual context, available modeling tools, solving algorithms, the accuracy required, possible simplifications, etc. Once the optimization problem model for the planning of a microgrid has been conveniently formulated and built, a suitable optimization algorithm must be implemented to find the optima of the model and solutions to the constrained optimization problem. Consequently, the optimal solutions are found over the optimization model, which may significantly vary from the actual planning problem. Hence, the definition of a microgrid's planning methodology becomes an iterative task where the optimization problem models must be evaluated and re-adjusted in a pos-optimality analysis in terms of the appropriateness of the optimal solutions in the context of the planning problem (Branke *et al.*, 2008).

The optimization planning problem of microgrids involves normally multiple (normally contradictory) linear and/or nonlinear objectives and equality/inequality constraint functions that are mostly influenced by the power flow equations and will give rise also to non-convex optimization problems. Furthermore, the decision (planning) variables will include discrete locations and sizes of non-modular components, continuous sizes for modular components, and binary variables for operating conditions (e.g. switches positions, demand management, etc.). Consequently, the planning methodology will deal with complex multi-objective, mixed-integer, non-convex combinatorial optimization problems, which are normally difficult to solve using conventional deterministic mathematical approaches. Therefore, the search and evaluation of proper optimization formulations and advanced solving tools have become

Table 1-1.: Differences between the traditional and microgrid planning problem. Adapted from Ghadi *et al.* (2019) and Xiang *et al.* (2016)

Feature	Traditional planning problem	Microgrid planning problem
Basic data management	Basic data processing based on the power production management system	Big data resource management in control center, including big customers' electricity habits, real-time measurement data, weather data, etc.
Planning and operation	Low penetration of DERs; worst-case planning; network solution only; fit-and-forget approach; deterministic approach; cost-effectiveness modeling	High penetration of DERs; combined planning and operation; capability for the active management of power loss and voltage profile; capability to provide new ancillary services in commercial scales; primary allocation and second control together; probabilistic approach; risk analysis is integrated with the modeling; full consideration of uncertainties; multicriteria modeling; islanded and grid-connected operation
Network structure	Fixed network, manual adjustment if needed	Flexible and configurable network structure relying on the strong communication automation and power-electronics-based system.
Communications and monitoring structures	Centralized information; little information exchange; low monitoring and control capabilities	Decentralized information; interactive information exchange; collaborative data exchange; increased monitoring, simulation, and control down to low voltage
Simulation	Time segment (typical value); mainly centralized, series-operation	Time window (series value); mainly distributed, parallel-operation
Optimization	Global optimization based on historical data and forecast data	Combines the global optimization and local autonomy control, integrated with real-time operational information

imperative for the research topic (Contreras *et al.*, 2020b; Alarcon-Rodriguez *et al.*, 2010)[1]. The necessity of considering multi-objective approaches to solve real-world optimization problem has been identified and explained in detail in several research literature (Branke *et al.*, 2008). These requirements have been also expanded to the microgrid's planning research area, where many authors have highlighted the existence of several conflictive objectives that must be considered during the planning stage (Kumar Verma *et al.*, 2019; Li *et al.*, 2017; Alarcon-Rodriguez *et al.*, 2010). However, the increase in the amount of research with multi-objective approaches is a relatively new trend in the ADN and microgrids planning strategies, as it can be concluded from the comparisons of literature review papers in the last five years (Kumar Verma *et al.*, 2019; Emad *et al.*, 2019; Georgilakis and Hatziargyriou, 2015; Gamarra and Guerrero, 2015). Kumar Verma *et al.* (2019) claim that the literature review regarding the usage of objective functions for the distribution network expansion problem reflects the increasing shifting from single-objectives to multi-objectives approaches. However, it can be also analyzed that several proposals have dealt with multiple objective planning models by means of transforming the multi-objective model into a virtual single-objective model based on weight coefficient methods (Li *et al.*, 2017; Emad *et al.*, 2019). Nonetheless, Alarcon-Rodriguez *et al.* (2010) and Branke *et al.* (2008) have earlier described the powerful advantages of a true-multi-objective approach, where the outcome is not a unique single solution but a set of mathematically equally good solutions known as Pareto optimal solutions. Thus, the most important advantage of a true-multi-objective method is the introduction of *a posteriori* articulation of preferences (Li *et al.*, 2017). This is possible since all the objectives are taken into account with equal consideration to find first a Pareto optimal solution set, which gives an overview of different solutions available and the possibility for the decision-maker to select the most preferred one among them (Branke *et al.*, 2008, Chapter 1).

Li *et al.* (2017) review several papers for the optimal planning of ADN and claim that more than 68% of the proposed methodologies adopted a multi-objective strategy to model and solve the optimization problem. Furthermore, Kazmi *et al.* (2017a) present a review of several distribution network planning techniques based on multi-objective optimization and identified several potential future research areas such as microgrids planning together islanded operation, active management, integration of operation features into planning, parameters tuning in multi-objective optimization algorithms were identified.

Considering the aforementioned context regarding the existence of multiple normally contradictory planning objectives, the doctoral research was planned to consider multiple planning objectives and use metaheuristics to solve the optimization problem. Several possible planning objectives have been identified in the literature, and their selection and utilization is still a research matter with open questions that might require several hours of investigation.

[1]This nature is shared with the planning problem at the transmission level, where it is also normally a mixed-integer, non-linear, non-convex optimization problem which aims to optimal selection of the routs, types, and number of the new circuits to be added in order to face the future demand (Ude *et al.*, 2019).

For example, an overview of possible objective functions for the planning of ADN is shown in Figure **1-1** (Kazmi *et al.*, 2017a; Li *et al.*, 2017).

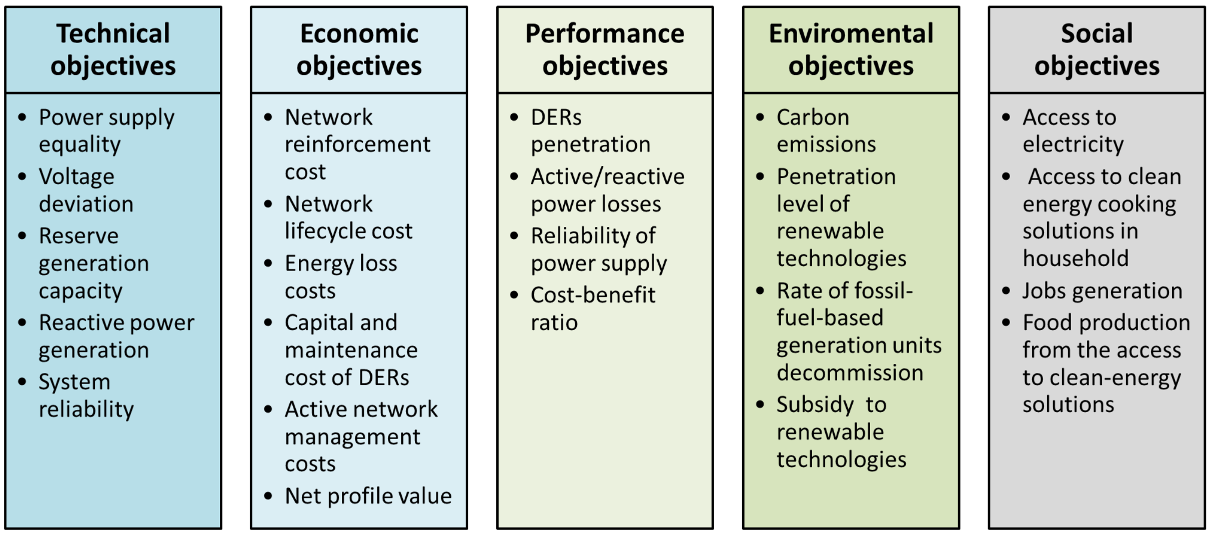

Figure 1-1.: Overview of possible objectives for the SPC planning

One of the main tasks in the microgrids planning problem is the optimal allocation (place and size) and selection of different technologies of DERs for the adequating of future microgrids. The allocation of generation resources is a well-known planning issue at the transmission level (Seifi and Sepasian, 2011). However, the strategies must be reevaluated for the allocation of DERs in the microgrid planning methodology, where several new characteristics, different operation conditions, impacts, and benefits such as the capacity of supplying ancillary services (AS) from the distribution network must be considered (Cardoso *et al.*, 2017; Majzoobi and Khodaei, 2017; CIGRE WG C6.22, 2015a). In this direction, there have been several publications and proposals to achieve an optimal allocation of DERs. For example, the location, size, and type of DERs were included as decision variables in around 34% for dispatchable DG, 30% for renewable DG, and 21% for centralized/distributed ESS of the literature survey conducted by Li *et al.* (2017). Surprisingly, at the same time, sizes of existing feeders and substations for reinforcements and location and sizes of new feeders were included in the planning problem in the 36%, 24% and 30% of the literature survey, respectively, which showed a characteristic of former strategies to tackle demand and expansion issues. However, a more recent review paper by Agarwal and Jain (2019) showed how the integration of DERs, and with this the imminent decentralization of the power systems, has attracted the attention of researchers.

The decision making for the allocation of DERs in the microgrid has led to finding strategies for properly modeling different distributed generation and storage technologies as part of the optimization problem. For example, microgrids will comprise a mixed generation matrix with both dispatchable and stochastic renewable non-dispatchable DGs (Ehsan and Yang, 2018). Furthermore, microgrids will incorporate ESSs (Saboori *et al.*, 2017), a power-electronic-based operation (Parhizi *et al.*, 2015), options for hybrid AC-DC architectures (Unamuno and Barrena, 2015) and possible application in multi-energy systems (Mancarella, 2014). Consequently, time-depended operational conditions (e.g. Active management for charging/discharging cycle of the ESS) and high-level uncertainties will be also part of the microgrid planning problem.

The operation characteristics of the microgrid become relevant for the planning task since the active management of DERs introduces the capacity of controlling and managing DGs, ESSs, and loads cooperatively to achieve the potential benefits of the microgrids (Li *et al.*, 2017). Consequently, distribution operation and planning stages cannot be longer considered as disconnected tasks, since the exploitation of existing and future assets with high automation and control capacities may be a valuable alternative to network expansion or reinforcement (CIGRE WG C6.19, 2014). Additionally, the massive integration of different types of power-electronic-based DGs (with high renewable penetration) will affect the reactive power flow in the power systems, and generate bi-directional fault currents that will perturb the system's security, which is also operational features that must be taken into account (Li *et al.*, 2017). Furthermore, it has been well discussed, e.g. (CIGRE WG C6.22, 2015a), that microgrids will be able to be planned with a capacity to provide AS on a commercial scale (Majzoobi and Khodaei, 2017). Hence, not only the technical impacts of an effective AS provision but also revenue streams resulting from the participation in AS markets, must be considered from the planning stage. For example, Cardoso *et al.* (2017) consider the effect of the AS as part of a Distributed Energy Resources - Customer Adoption Model DER-CAM. The results showed that the participation of ADNs in AS markets can significantly affect the optimal sizing of resources as well as the dispatch of energy. Nonetheless, the ability to provide AS has not been typically considered in DERs sizing problems (Li *et al.*, 2017; Ghadi *et al.*, 2019; Xiang *et al.*, 2016), which is a disadvantage of existing planning methodologies concerning the modern necessities (Cardoso *et al.*, 2017).

The integration of microgrid's operational behavior as part of the planning stage can be seen as a consequence of the unquestionable necessity of more comprehensive planning methodologies as was mentioned before. In the same direction, traditional planning problem has been normally addressed in parts or stages (Seifi and Sepasian, 2011). For example, the generation expansion planning has been managed in a separate planning stage than the network expansion planning that comprises the topology planning. However, microgrids' topologies will have a relevant role in the microgrid's performance as it is claimed by Cortes, Contreras and Shahidehpour (2018) and Che *et al.* (2017b). Furthermore, the network operators will have the option of managing the power flows using flexible network topologies (CIGRE WG C6.22, 2015a), and the planning of networking microgrids will require a proper clustering strategy from the planning stage (Contreras *et al.*, 2020b; Alam *et al.*, 2019). However, topology planning is not a simple task. For example, topology can be planned from the binary connection/disconnection of the different lines/cables routes that will bring about binary decision variables as part of the optimization problem definition (Contreras *et al.*, 2020b; Gazijahani and Salehi, 2018b). Furthermore, there will be a mutual influence between the topology and other elements of the microgrid, which for example can be the allocation of renewable resources with stochastic nature.

Integration of stochastic renewable distributed generation, active dynamic loads, active participation of the demand side in open markets and the implementation of demand management strategies introduce a comprehensive amount of high-level uncertainties [2], which have a great impact on the planning models and solving algorithms (Li *et al.*, 2017). Uncertainties in microgrids are mostly created due to stochastic environmental/behavioral events and/or failure of system components, which will define a planning scheme and the selection of a modeling technique. For example, Gholami *et al.* (2016) categorize the microgrid uncertainties into two groups:

- Normal operation uncertainties, e.g. uncertainty of renewable resources, load variations, and real-time market prices.
- Contingency-based uncertainties, e.g. randomly forced outages, unintentional islanding, and resynchronization events.

Several uncertainties modeling techniques such as probabilistic techniques, multi-scenarios based approaches, stochastic optimization, or robust optimization techniques have been studied and proposed in literature (Ehsan and Yang, 2019; Aien *et al.*, 2016), although the selection of the appropriated technique for a particular planning problem is still a complex question to be solved by research. Furthermore, despite the different sources of uncertainty such as normal operation uncertainties, and contingency-based uncertainties (Gholami *et al.*, 2016), existing planning methodologies consider normally only a group of them. Examples of this approach can be found in (van Bracht *et al.*, 2016) where authors propose a method for the optimal generation expansion planning under long-term (strategical) and short-term (operational) comprehensive economical and technical uncertainties in normal operation conditions, or in (Khodaei *et al.*, 2015), where models for the planning of microgrids under uncertainty are proposed for determining the generation mix of DER considering both grid-connected and islanded operating modes under incidents. Uncertainties are modeled with stochastic scenarios and robust optimization by van Bracht *et al.* (2016) and Khodaei *et al.* (2015), respectively. Therefore, there is an inherent necessity of future enhancements to some existing proposals, where a more comprehensive view of the possible uncertainty sources and the use of more conveniently uncertainties modeling techniques are required.

[2]Note that the level uncertainty is the level of accuracy with which an input parameter of the planning problem can be forecasted (Ehsan and Yang, 2019). High-level uncertainties refer to multiple uncertainties that coexist and interact to create a situation that is in practice impossible to predict and a range of possible outcomes cannot be established.

In summary, it is evident that the optimal planning of microgrids is an intricate problem that involves several components with complex mathematical models, high-level uncertainties, multiple and normally contradictory design objectives, different types of decision variables, numerous constraints, variable market/regulation conditions, highly planning-sensibility to operation features and a bigger diversity of stakeholders. Furthermore, it is clear that despite the considerable increasing amount of research that has dealt with these issues of the planning problem (e.g. components' models, uncertainties etc.), some have not been properly resolved so far and in general, the research has been mainly addressed in a relatively separated and highly case-depended way, which have led to maintain until today several gaps in the state of the art that must be filled in. For example, state of the art shows that the prior work on microgrid planning is limited and the existing studies often omit some important factors in the planning process, such as key operational factors and microgrid benefits (e.g. AS provision), data uncertainty, multiple objectives, topology planning or grid-connected and islanded operation modes. This doctoral thesis aims to contribute to close the gaps in the state of the art at addressing the need for efficient and viable microgrid planning methodologies. The applications of a true-multi-objective and suitable high-level uncertainty modeling techniques in a comprehensive model for the planning of microgrids under the paradigm of ADN with capacity for providing AS would supply sufficient resources over traditional planning strategies for giving rise to the required future planning methodologies. For that purpose, the research questions that have motivated this doctoral research and the objectives that have been carefully formulated to answer those inquires are described in the following section.

1.3. Research objectives and questions

Technical- and cost-effective integration of DERs into the current distribution networks is essential to achieve the secure, reliable, efficient, and sustainable power delivery goals. This doctoral research was proposed over envisioning microgrids as powerful concepts that will be essential for the construction of the power system of the future. Therefore, utilities and stakeholders require novel and solid planning methodologies to guarantee an optimal transition and future operation of microgrids. This thesis has the aim to contribute to the state of the art with explicit knowledge for effectively tackling the decision-making problem for the optimal expansion planning of existing MV utility microgrids or the transformation of passive or active MV distribution networks into them [3]. Consequently, the main purpose of the doctoral thesis is to propose a comprehensive methodology for the planning of microgrids that considers key features such as a multi-objective approach, high-level of DERs

[3] For this dissertation, the term **microgrid** will be used instead of utility microgrid, community microgrid or milligrid. The purpose of this connotation is to consider the microgrid general concept at every time even when the methodologies and models here described and used were mainly adopted under the paradigm of MV utility microgrids.

penetration, ESS technologies, uncertainties in the planning and the topology of the microgrid. The methodology is intended to become a useful planning tool to first, optimally find a set of possible Pareto solutions to the microgrid's planning, and secondly to offer a set of alternatives to the stakeholders for accomplishing a final decision making based on their preferences for the solution to the planning problem.

Research questions

Based on the research problem that motivated this investigation, this doctoral thesis aims to answer the following research question:

> **How effectively can the microgrid power resources be optimally planned with multi-objective optimization if the topology of the network and a high penetration level of renewable resources and distributed storage systems are considered?**

To answer this question, it is important to perform several activities that should take into account the following questions:

(RQ1) Which type of performance characteristics of the microgrid can be used as part of the objective functions for the true-multi-objective optimization problem formulation?.

(RQ2) How can a proper mathematical model of the microgrid be defined to include all the required components, uncertainties, and dynamics of the problem?.

(RQ3) How can the microgrid's topology and high penetration of renewable resources with stochastic operation be considered as part of a planning methodology?.

(RQ4) Which optimization algorithm is suitable to solve a true-multi-objective optimization problem of this nature?.

To find a solution to these research questions, the research objectives of the doctoral thesis are formulated as follows.

General objective

This doctoral thesis aims to

> **develop a multi-objective power resources planning method based on the microgrid topology optimization and considering a high penetration of intermittent nature generation and modern storage systems.**

The research objective is originated from the shortcomings found in existing MV or utility microgrid planning methodologies in the state of the art. The fulfillment of this objective is intended to obtain a suitable methodology for the allocation of power resources such as dispatchable DGs, non-dispatchable renewable DGs, and distributed ESS. Furthermore, the resulting methodology from the general objective includes also the microgrid's topology definition in order to offer a holistic approach to the microgrid's planning problem. To this end, the aforementioned planning problem is studied and a true-multi-objective microgrid planning methodology is proposed considering three possible technical and economical objective functions. The planning methodology focuses on including key technical microgrid's aspects such as the presence of high-level uncertainties and the paradigm of microgrids with AS supplying capacity.
For that purpose, the specific research objectives should be accomplished.

Specific Objectives

(SO1) To formulate an appropriate set of objective functions, decision variables, and constraint functions for the power resources planning optimization problem.

(SO2) To develop the mathematical model of a general microgrid with high penetration of intermittent nature distributed generation resources and novel storage energy systems.

(SO3) To include the microgrid topology effect and microgrid performance indexes as part of the power resources planning problem both in grid-connected and islanded mode.

(SO4) To select and suit an optimization method to solve the multi-objective power resources planning problem considering the topology and components size and location in the microgrid

From the identification of the research problem, formulation of the research questions and establishment the doctoral thesis' objectives, the two working hypothesis below are assumed as premises for the current investigation.

Hypothesis 1 -(HS1)
A microgrid planning methodology based on a multi-objective optimization model gives rise to a wider overview of the range of decision-making options, which is necessary for enhancing the microgrid's benefits and impacts.

Hypothesis 2 -(HS2)
A more comprehensive holistic approach for planning simultaneously the DERs location and capacity together the microgrid's topology will lead to remarkable planning advantages compared with traditional planning strategies.

1.4. Main contributions and highlights of the research

The main outputs of this doctoral thesis are the two versions POMMP and POMMP2 of the probabilistic multi-objective microgrid planning methodology. The methodologies were developed and proposed based on the identified research problem with the aim to close gaps in the state of the art with explicit knowledge in the planning of microgrids topic. Within this intention, the main contributions and highlights for this doctoral research are listed and shortly described below to facilitate the comprehensions of the original inputs of this research and highlight relevant features and novelty key proposals in this dissertation.

- The POMMP and POMMP2 methodologies are formulated as true-multi-objective optimization planning problem with three technical and economical objective functions for the planning of MV microgrids and networked microgrids under the paradigm of microgrids with capacity for supplying AS based on a fully available extra active power capacity to be exported back to the main grid and provide spinning and non-spinning operating reserve as well as up- and down-frequency regulation based on the active management of DERs such as ESS. The true-multi-objective approach allows the *a posteriori* analysis of all optimal alternatives (solutions) for the decision making. Numerical results demonstrate the relevance of considering available reserve power for providing AS from the planning stage, as well as the benefits of a true-multi-objective approach for proper exploitation and assessment of the microgrid's benefits in terms of their technical impacts and revenues from the participation in the services market.

- The grid-connected and islanded operation modes are considered from the microgrid's planning stage in both POMMP and POMMP2 methodologies. As it is carefully described in this dissertation, one of the most representative features of the microgrids compared with other ADNs is the islanding capability. The POMMP and POMMP2 methodologies consider novel strategies to incorporate the operational modes from the planning stage to guarantee optimal planning of power resources and topology together capacity of supplying AS under an efficient, affordable, and profitable condition. The proposal of considering power mismatch in islanding operation mode from the planning objectives and contemplate different islanding conditions in networking microgrids have been never proposed before in the literature. Simulation results show the advantages of these two strategies for solving the planning problem.

- The POMMP2 methodology proposes a novel holistic approach to consider together the allocation of DERs and topology definition in a cluster-based networked microgrid planning under the paradigm of microgrids with capacity for providing AS from reserve power. Therefore, a novel strategy to include a multilevel graph-partitioning technique for the optimal formation of clusters in the planning of networked microgrids is proposed for the first time in this doctoral research. With this strategy, a flexible planning setup is provided form planning full radial-based, loop-based, mesh-based, or mixed topologies. It was found from results that the strategy offers advantages regarding traditional separated approaches for maximizing the benefits of the microgrids implementation.

- The high-level uncertainties in the planning of microgrids are considered. For that purpose, a probabilistic approach and Monte Carlo Simulation are considered for the non-dispatchable DG units and load models. Despite the uncertainties modeling technique is not a contribution of this doctoral research, the use of this technique as part of novel methodologies as POMMP and POMMP2 for the first time will offer a research comparative base-case for future research in the evaluation and modeling of high-level uncertainties for the planning of microgrids. Furthermore, it is once more demonstrated the unquestionable necessity of considering uncertainties properly as part of any microgrid planning methodology.

- Economical aspects are properly adapted and included in the POMMP and POMMP2 methodologies to model and consider the AS market conditions during the microgrids planning stage. The economic objective function minimizes the investment, operation, and maintenance cost of the microgrid, while the revenues from power exportation and services provision are taken into account.

- The decision-making stage is also included as part of the POMMP and POMMP2 methodologies. Several research omit this step, which is also relevant to proportionate an applicable strategy in real engineering problems. Consequently, a decision-making stage based on the analytic AHP technique is implemented to properly choose an optimal microgrid design from the Pareto-set. The decision-making technique is carefully chosen based on the study of the state of the art, and parallel research linked to this doctoral thesis.

- Although demand response is not deeply explored as part of the planning methodologies in the current doctoral research, POMMP and POMMP2 are formulated with the capability of considering some basic strategies such as load-shedding for islanded operation during contingencies. The strategy is evaluated in terms of the capacity to plan available residual power for the provision of services during normal grid-connected operation of the microgrid.

- Different case studies and solving metaheuristic optimization algorithms are evaluated and compared as part of the research.

The research was developed in four work packages, Figure 1-2.

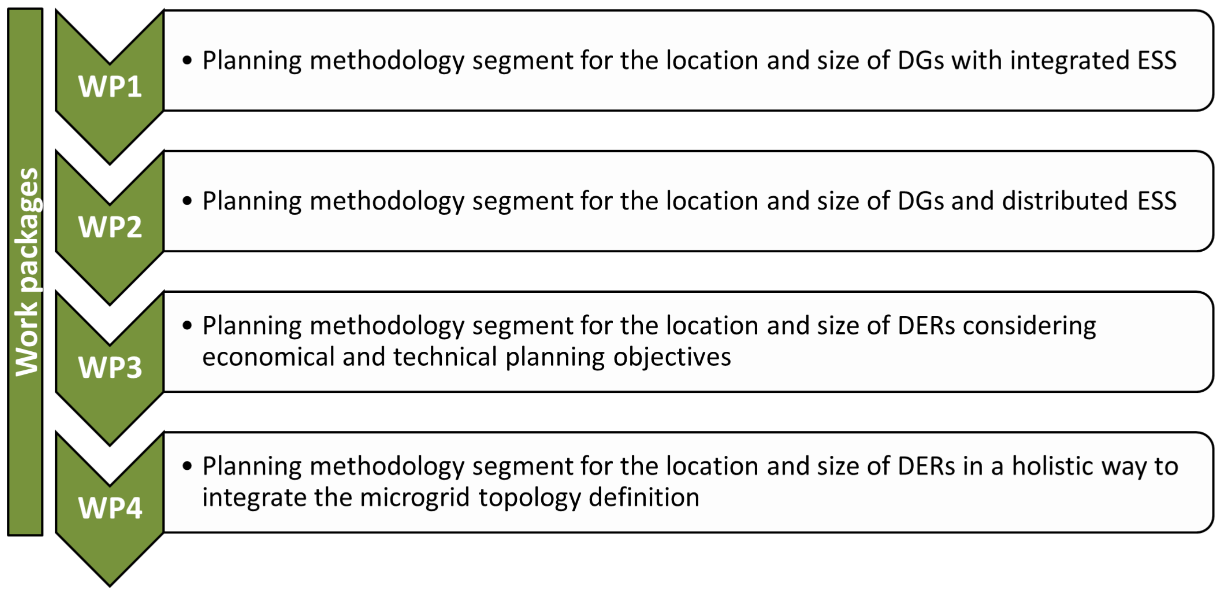

Figure 1-2.: Doctoral research work packages

Main results of the WP1 offered ground knowledge to clarify the research problem, terms, concepts, and methods for the following work packages. The results were presented in the international conferences listed below.

- Contreras, S.F., Cortes, C.A. and Myrzik, J.M.A. (2018). "Multi-Objective Probabilistic Power Resources Planning for Microgrids with Ancillary Services Capacity", In 2018 Power Systems Computation Conference (PSCC). pp. 1–8. doi: https://doi.org/10.23919/PSCC.2018.8450878.

- Acosta, A.F., Contreras, S.F., and Cortés, C.A. (2018). "Performance Assessment of a Modified Multi-objective Cuckoo's Search Algorithm for Microgrid Planning Considering Uncertainties". Proceedings of the Genetic and Evolutionary Computation Conference Companion on - GECCO'18, 276–277. doi: https://doi.org/10.1145/3205651.3205728.

The results in the WP2 of the doctoral research paved the trajectory for the models and approaches that were implemented in the WP3. The main results of the WP3 were presented in the journal and international conferences listed below.

- Contreras, S. F., Cortes, C. A. and Myrzik, J.M.A. (2019). "Optimal microgrid planning for enhancing ancillary service provision", Journal of Modern Power Systems and Clean Energy, Vol. 7, No. 4, pp. 862–875. doi: https://doi.org/10.1007/s40565-019-0528-3.

- Rodriguez, M.A., Lopez, D.F., Contreras, S.F., Cortés, C. A. and Myrzik, J.M.A. (2020). "Performance Evaluation of the MOEA/D Algorithm for the Solution of a Microgrid Planning Problem," In Proceedings of the Genetic and Evolutionary Computation Conference Companion on - GECCO'20, pp. 173-174. doi: https://dl.acm.org/doi/abs/10.1145/3377929.3390036.

- Penaranda, A.F., Mosquera P.E., Contreras, S.F., Cortes, C.A. and Myrzik J.M.A. (2019). "Planning Model of Microgrids for the Supply of Ancillary Services to the Utility Grid", In 2019 IEEE Milan PowerTech. IEEE, pp. 1–6. doi: https://doi.org/10.1109/PTC.2019.8810998.

The Probabilistic Multi-objective Microgrids Planning Methodology (POMMP) was proposed in (Contreras *et al.*, 2019). Furthermore, the results in the WP3 contribute to finding a solution to the (RQ1),(RQ2), (RQ4) and accomplishing the specific objectives (SO1), (SO2), (SO4).
The research in WP4 was the extension of the work in WP3. A second version of the Probabilistic Multi-objective Microgrid Planning methodology, called POMMP2, was proposed in this work package to find a solution to the microgrid's topology planning problem as part of a holistic approach to planning problem. The main results were presented in the journals listed below.

- Contreras, S.F., Cortes, C.A., and Myrzik, J.M.A. (2020). "Probabilistic Multi-objective Microgrid Planning Methodology for Optimizing the Ancillary Services Provision". Electric Power Systems Research, Vol. 189, pp. 106633. doi: https://doi.org/10.1016/j.epsr.2020.106633.

- Cortes, C. A., Contreras, S. F., and Shahidehpour, M. (2018). "Microgrid Topology Planning for Enhancing the Reliability of Active Distribution Networks." IEEE Transactions on Smart Grid, Vol. 9, No. 6, pp. 6369-6377. doi: https://doi.org/10.1109/TSG.2017.2709699.

During preliminary research, the topology planning based on graph partitioning theory was studied by us in (Cortes, Contreras and Shahidehpour, 2018). This strategy was adopted and adapted for the POMMP2 methodology, whose results are presented by us in (Contreras *et al.*, 2020b). The models, optimization problem, and planning of the WP4 were intended to offer an answer to the research question (RQ3) and consequently accomplish the specific research objective (SO3). Moreover, conclusions from the WP4 allowed the analyses and evaluation of the assumptions in the (HP2) regarding the benefits of a holistic approach for considering topology in the planning of microgrids. Furthermore, due to the enhancements to the POMMP methodology in WP4, the outcomes of the work package also complemented the achievements in WP3 in all the research questions and objectives.
A deeper explanation, discussion, and argumentation to support the claims here presented will be given along chapters in the dissertation.

1.5. Outline of the dissertation

This dissertation is formed by seven chapters including this introductory Chapter 1, where the context and motivation for the proposal and execution of the current doctoral thesis were described.

The remainder of the dissertation is organized as follows:

In Chapter 2 the current context for the power and distribution systems is presented once more with the aim to properly define the microgrid concept and describe its classification based on relevant studies in the literature. This component in the dissertation deserves special attention for the further discussion of the different models and methods in the doctoral thesis. It is important to clarify and describe the global constructive and operational characteristics of the microgrids as well as the different types of microgrids and their particular features. These detailed characterizations are found in Chapter 2. Furthermore, the benefits and impacts of the microgrids implementation, the revenues from the microgrid services supplying (e.g. AS provision), and a review of the state of the art regarding the microgrid's planning problem, multi-objective optimization strategies and supplying of AS by microgrids are presented in Chapter 2 as well.

Chapter 3 describes in detail the operational characteristics and adopted/developed mathematical models for the proposed planning methodologies in this dissertation. For example, the mathematical model for integrating the operational behavior of different DERs in the microgrid such as dispatchable and non-dispatchable DGs technologies, distributed ESSs with and without active management strategies, as well as models for considering grid-connected and islanded operation modes, models to consider uncertainties in the generation and load demand are presented in this chapter. Furthermore, the mathematical models and strategies to contemplate the markets' behavior and in particular the AS market's characteristics are also explained in this chapter. Most of the content in this chapter offers answers to the research question (RQ2) in order to achieve the specific research objective (SO2). The POMMP2 methodology includes holistically the effect of the topology planning into one single approach. Therefore, in Chapter 3 the required mathematical models and multi-level graph partitioning technique used in POMMP2 methodology to optimally define clusters in a networked microgrid and afterward their topology structure is described. This part of the dissertation is intended to offer an answer to the research question (RQ4) and contribute to achieving the research goal (SO4).

The true-multi-objective optimization problem used both POMMP and POMMP2 methodologies are explained and characterized in detail in Chapter 4. In this chapter, the definition of the optimization problems with their configuration alternatives is described. Therefore, a set of mathematically defined technical- and economical-based objective functions, sets of decision variables vectors, and constraint functions are found in Chapter 4. This content of the dissertation has the purpose of answering the research question (RQ1) and fulfill the specific research objective (SO1). Furthermore, a general description of the required metaheuristics for the solution of the multi-objective optimization problem is also exposed. In this case, the studied state of the art in Chapter 2 regarding used optimization algorithms for the microgrid's and ADN's planning problem is taken into account for the selection of suitable optimization algorithms to solving the proposed optimization problem in this dissertation. Consequently, the optimization algorithms are sufficiently explained in Chapter 4 to facilitate readers to comprehend the POMMP and POMMP2 planning methodologies in Chapter 5. Two indicators, hypervolume and coverage factor, are implemented to evaluate the performance of the optimization algorithms for solving the microgrid planning problem. The output in this chapter contributes to answer the research question (RQ4) and accomplish the research goal in (SO4). The final step in the planning methodologies is given to the decision making process for the selection of a single optimal planning solution. Therefore, a multi-criteria decision making is necessary. In Chapter 4 the selection of AHP technique for the decision making in the proposed microgrid planning methodology will be presented and the algorithm is detailed for its further utilization.

Once the mathematical models and optimization problem have been previously explained, the probabilistic multi-objective microgrid planning methodologies POMMP and POMMP2 are presented and disclosed in detail in Chapter 5. In this chapter, the different steps, methods, principles, and rules of the POMMP and POMMP2 methodologies for addressing the optimal microgrid planning problem are described. In this chapter, the individual requirements for conforming the microgrid planning methodology are integrated in order to accomplish the main objective of this doctoral thesis.

Chapter 6 focuses on the formulation, parameter tuning, execution and results of simulations to test the proposed planning methodologies, which is managed based on two case studies.

- **Case study 1 - (CS1):** Microgrid planning for the PG&E 69-bus medium voltage distribution network
- **Case study 2 - (CS2):** Microgrid planning for the IEEE 37-bus medium voltage distribution network

The chapter can be outlined in two parts. In the first part, simulation parameters and configuration are carefully described. Furthermore, a procedure for the parameter tuning of the optimization algorithms is shown in this part of the chapter as well. In the second part, simulation outcomes and result analysis are presented for each case study. In this vein, Pareto optimal sets are found as solutions to the microgrid planning problem for each case study. Furthermore, the possible solutions are analyzed and compared in terms of the objective functions and microgrid's indirect operational performance characteristics to the selection of a single solution through the established multi-criteria decision making strategy. The numerical and simulation results presented in this chapter aim to demonstrate the effectiveness of the proposed POMMP and POMMP2 methodologies and provide concrete information to accomplish the main doctoral thesis objective and offers a solid answer to the main research question that motivated the current research.

The conclusions of the doctoral research and recommendation for future research are formulated in Chapter 7. In this chapter, a discussion of the most relevant contributions of the research and possible improvements for future research are offered. Finally, five appendixes present supplementary material to complement the main components of this dissertation and offer relevant information for deeper understanding, reproduction, or expansion of the current doctoral thesis achievements in the future.

2. Microgrids as part of the power systems of the future

Electric energy has positioned as one of the main pillars of modern society, being its versatility and well established knowledge, two of the main aspects that boosted its fast development and use during the last century (Glover and Sarma, 2003, **Chapter** 1). For example, advances in the three-phase AC power technologies and theory led to the settlement of the AC as the transmission standard for decades and gave rise to a centralized and uni-directional power delivery in the called conventional power systems.

This chapter has the purpose to deepen in the concept of ADNs and microgrids, as well as present in detail the current state of the art in the planning of microgrids. Section 2.1 describes the concept of ADNs, while a detailed explanation of the microgrid concept, types, architecture is shown in Section 2.2. A brief description and review of the main stakeholders, actors, and possible ownership of microgrids are described in Section 2.3. The next two sections, Section 2.4, and 2.5 describe the benefits and impacts from the advantages of implementing the microgrid concept, and challenges or barriers due to the disadvantages of the current context associated to the concept. Based on the discussion in previous sections, Section 2.6 presents a thesis on the future microgrids planning methodologies from the current challenges for a massive deployment of microgrids. These statements lead to a short explanation of the current and future AS in the electric markets in Section 2.7 and a presentation of the current state of the art in the microgrid's planning problem, where the main goal is to identify and show last proposals with their advantages and disadvantages in the last section of the chapter, Section 2.8.

2.1. Transition to the active distribution networks

Conventional power systems are characterized by a centralized architecture, where the electrical power is generated in a set of large power plants, to be delivered through the transmission and distribution systems to the end-users, which are normally located far away from the generation point (Kwasinski *et al.*, 2016, Chapter 1). Electricity has been traditionally produced by high scale electromechanical generators that are propelled by turbines to transform fossil-fuels, nuclear or flowing water primary energies. However, major problems in last decades such as a steady depletion of fossil fuel resources, threats from nuclear power operation, climate phenomena that have given rise to severe shortages in the water reservoirs,

low energy efficiency, high reliability demand and environmental impacts due to greenhouse gas emissions, ecosystems pollution or radioactive nuclear waste problem, have led to deeply reevaluate the future of the power systems (Chowdhury *et al.*, 2009, Chapter 1).
In this way, conventional power systems are transforming in an unprecedented way due to decentralization and decarbonization, which has given rise to the major transition era from passive distribution networks with centralized generation and unidirectional electricity transmission, to active distribution networks with decentralized generation and bidirectional electricity transportation (Chowdhury *et al.*, 2009, Chapter 1), Figure **2-1**.

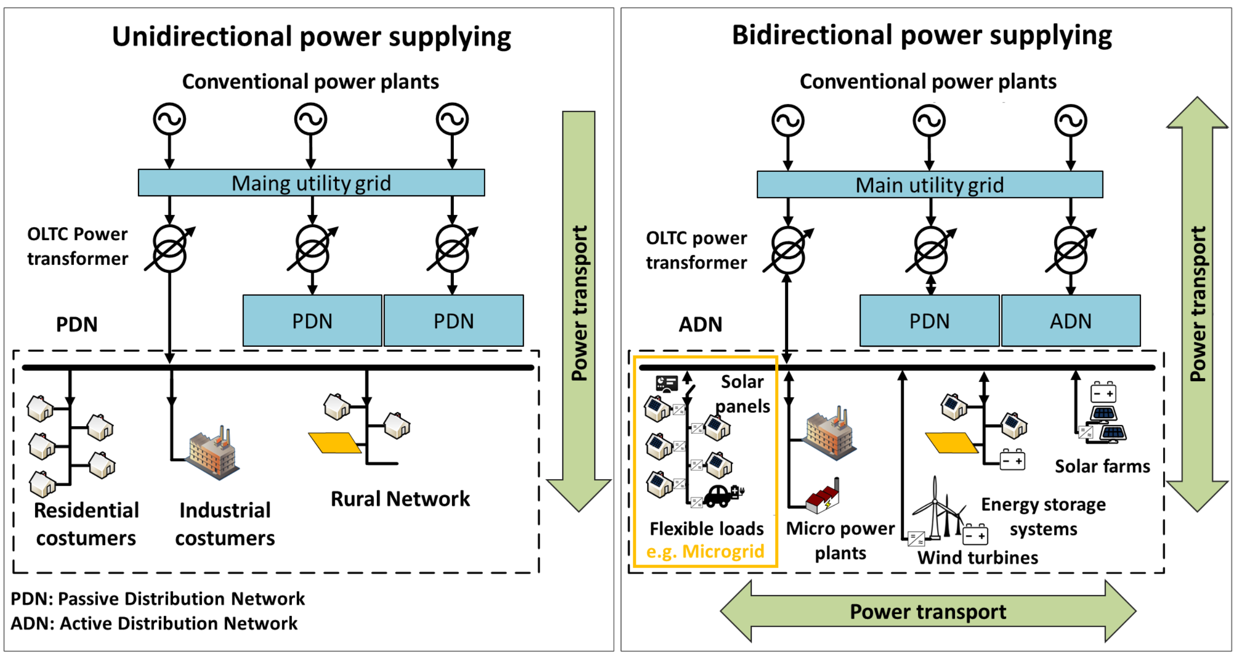

Figure 2-1.: Transition from an unidirectional to a bidirectional power supplying in the power systems

The type of non-conventional and/or renewable generation sources located close to end-users and with lower capacities than conventional generators, are defined as Distributed Generation (DGs) sources. Some DG sources are micro-turbines, stirling generators, combined heat and power (CHP) co-generators, fuel cells etc., which are propelled by primary energies such as natural gas, biogas, biomass, diesel, etc. On the other hand, the most frequently used renewable generation technologies are photovoltaic systems, and wind turbines (Chowdhury *et al.*, 2009, Chapter 1).
The integration of DG into current passive distribution networks has given rise to the aforementioned concept of ADN. Thus, the supply has gone from being based on unidirectional power transport from the large generators of the main utility intercontinental, national or regional network to the customers, to one with a bidirectional power flow to and from the customers concentrated in the distribution levels.

Additionally, one of the most critical factors in the supply of electric power is the difficulty and/or the costs involved in the storage of electric power and its use in later periods. However, the development of mobile technologies, electric vehicles and the penetration of DG such as photovoltaic cells and wind turbines, where the availability of their primary energy (solar radiation and wind speed) can not be controlled, have accelerated the advances and with this the integration of ESS in ADN. Some classic examples of ESS are the storage of energy in a chemical form with the batteries, in a kinetic form with the flywheels, in the form of static electricity with the super-capacitors, by potential power with the pumping of water at higher elevations and by pressure with the compression of air in underground reservoirs (Tan *et al.*, 2013). However, ESS such as battery systems have found their way into ADN by their ability to be installed near demand centers. To the set of DGs, ESS distributed, and demand management systems are known as DER (Chowdhury *et al.*, 2009, Chapter 1; Lasseter *et al.*, 2002).

The integration of DERs in the distribution networks and their operation has been possible due to the development of advanced communication and measurement systems and protocols, which has been known as smart grids (Smart Grids). In that way, ADNs are distribution networks that integrate distributed energy generation and storage systems that are operated with a high level of automation and advanced control, communication, and measurement strategies. However, a proper definition of an ADN is given by CIGRE WG C6.19 (2014):

> *"Active distribution networks (ADNs) have systems in place to control a combination of distributed energy resources (DERs), defined as generators, loads and storage. Distribution system operators (DSOs) have the possibility of managing the electricity flows using flexible network topology. DERs take some degree of responsibility for system support, which will depend on a suitable regulatory environment and connection agreement"*

With this, in the last three decades, ADN has been extensively researched by universities, industry, working groups and institutions with global influence such as the International Council of Large Electrical Networks (CIGRE), the energy department (DOE) of the USA, and the Consortium for Electrical Reliability Technology Solutions (CERTS), among others. Therefore, several specific definitions of DERs depending on the rated values, the voltage level, the countries and regions around the world, etc., can be found. However, the impact of DERs on the energy system is normally the same, regardless of these different definitions. In the same way, multiple concepts have been presented and have evolved in order to characterize in greater detail the design and operation of different ADN. An important concept is microgrids.

2.2. The microgrid concept

A simple definition of Microgrid can be given as a low or medium voltage ADN with autonomous control that operates both connected and isolated from the main power grid. However, the microgrid concept has not been fully defined yet, and its official definition and scope usually differs in literature (Martin-Martínez *et al.*, 2016). As a consequence, authors normally mention and apply the microgrid concept in slightly different ways (Martin-Martínez *et al.*, 2016) since the first mentions of a microgrid concept by Lasseter (2001) and Marnay *et al.* (2001).

For example, the Consortium for Electric Reliability Technology Solutions (CERTS) in the USA defines microgrids as "*aggregation of loads and microsources operating as a single system providing both power and heat. The majority of the microsources must be power electronic-based to provide the required flexibility to insure operation as a single aggregated system. This control flexibility allows the CERTS MicroGrid to present itself to the bulk power system as a single controlled unit that meets local needs for reliability and security*" (Lasseter *et al.*, 2002).

Other definitions can be also found in the literature. For example, Chowdhury *et al.* (2009) define a microgrid as "*a small-scale, LV CHP supply network designed to supply electrical and heat loads for a small community, such as a housing estate or a suburban locality, or an academic or public community such as a university or school, a commercial area, an industrial site, a trading estate or a municipal region*". Furthermore, the author mention that a microgrid is "*an active distribution network because it is the conglomerate of DG systems and different loads at distribution voltage level*". Kwasinski *et al.* (2016, Chapter 1) adopt the definition of the microgrid as "*a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid*".

In this way, the formal mirogrid definition adopted for this doctoral thesis is taken from the Technical Brochure of 2015 given by CIGRE Working Group C6.22 Microgrids Evolution Roadmap (CIGRE WG C6.22, 2015a):

> "*Microgrids are electricity distribution systems containing loads and distributed energy resources, (such as distributed generators, storage devices, or controllable loads) that can be operated in a controlled, coordinated way either while connected to the main power network or while islanded*".

The microgrid concept comprehends two main attributes. It includes local distributed energy resources (generation, storage and loads), which operate under local control, and can operate either in grid-connected or islanded modes. Accordingly, although the microgrid concept has been used generically to describe the changing grid paradigm, it can be seen that it might cover a wide range of designs in terms of configuration and characteristics (Marnay *et al.*, 2011).

Due to not having a globally accepted microgrid (or active distribution networks) classification so far, research on microgrids have to consider a possible range of application and specify the scope of the different design, operation, planning, etc., techniques and methodologies. For example, Farhangi and Joos (2019, Chapter 2) claim that the first step for the design of a microgrid is to select a benchmark model based on the type of microgrid (and associated business case) as reference. CIGRE WG C6.22 (2015a) describes a microgrid benefit quantification methodology based on the specification and assessment of business cases. The starting point of the methodology is the definition of the characteristics of a base case based on the type of microgrid.

Farhangi and Joos (2019, Chapter 2) mention that common types of microgrid are commercial/industrial microgrids, community/utility microgrids, campus/institutional microgrids, military microgrids and remote microgrids. This classification matches Lopes *et al.* (2013) one, who presented a general classification of microgrids based on the type of application, ownership structure and type of load. Consequently, microgrids can be classified into three main groups: utility microgrid (urban network or rural feeders), industrial/commercial microgrids (multi-facility or single facility) and remote microgrids.

Other references suggest a sub-division of the concept regarding the structure for the electricity generation and delivery systems. For example, Marnay *et al.* (2011) describe a possible structure where the traditional grid remains similar at a high voltage level and it is called the macrogrid, while three entities are added at the distribution level: community grids or miligrids that operates a portion of the existing distribution network, microgrids which are related to the costumer's sites and nanogrids such as telecom or Ethernet networks. To this type, two more have been added and described in (CIGRE WG C6.22, 2015a; Marnay *et al.*, 2015): isolated remote power systems and virtual microgrids.

Other complementary proposals for the microgrid's classification task have been presented. One example can be found in (Martin-Martínez *et al.*, 2016). Authors propose a classification of the microgrids according to four functional layers: Infrastructure, communications, intelligence, business models and regulatory framework. Furthermore, the functional layers are divided into three different levels based on the functionality inside of the microgrid concept: Microgrid, Nanogrid and Picogrid. In this case, Martin-Martínez *et al.* (2016) define Nanogrid as the grid of a building with DER, Picogrid as an aggregation of controllable loads in a household and Microgrid as the electricity grid that normally corresponds to a neighborhood, campus, etc., and is connected to the power distribution grid or another microgrid.

In this thesis, the following definitions are adopter for all purposes.

2.2.1. Types of microgrids

The types of microgrids described below are distinguished in (CIGRE WG C6.22, 2015a) and depicted in Figure **2-2** according to CIGRE WG C6.22 (2015a) and Marnay *et al.* (2011).

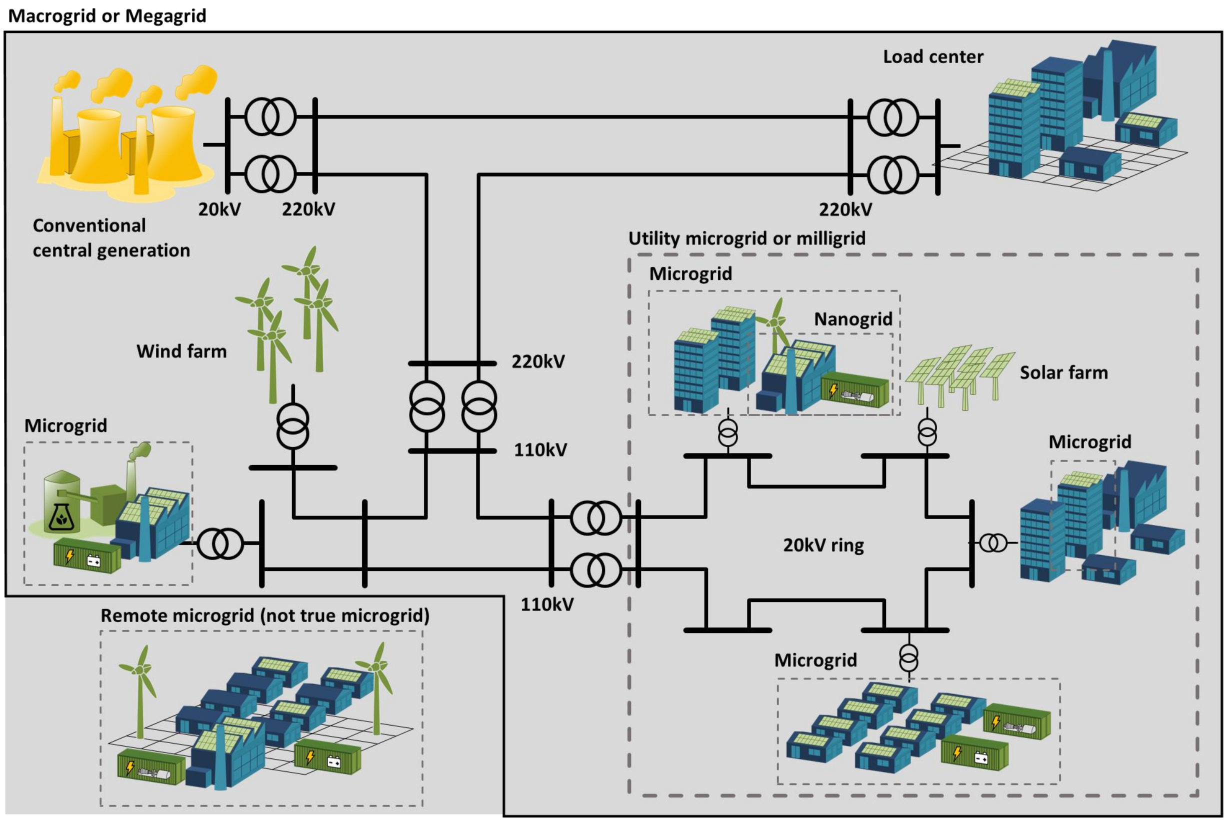

Figure 2-2.: Types of entities as a classification of microgrid types, adapted from Sinha (2016)

Customer microgrids or true microgrids: ($\mu grids$) are self-governed entities that are normally located downstream of a single point of common coupling (PCC) and are under the costumer's dominion. Hence, the restrictions for the microgrids implementation and operation are relatively lax. Most of the current benchmarks and regulatory structures are under this type.

Utility or community microgrids or milligrids: ($mgrids$) involve a segment of the regulated grid and include traditional utility infrastructure. Consequently, milligrids are mainly different from microgrids from the regulatory and business model viewpoint since the existing utility regulations (and codes) have a considerable role in the milligrids implementation and operation. Milligrids can operate as an actor in an active distribution network. The networking of multiple self-governed microgrids is a powerful concept that is known as networked microgrids and might be classified in this type of microgrids. However, the concept still requires intensive research for its practical implementation (Alam *et al.*, 2019).

Similar scale isolated remote power systems: ($rgrids$) involve similar technology to microgrids, however, they cannot operate in grid-connected mode and hence they might be considered as not true microgrids. Notwithstanding, microgrids currently use a large percentage of technologies that were tested and used the first time in remote grids. Therefore, from the research point of view, remote microgrids can be described as microgrids. Remote distribution grids have been operating for decades in countries with rugged terrain and not fully interconnected regions such as in Colombia (Gaona *et al.*, 2015).

Virtual microgrids: ($vgrids$) involve distributed energy resources that are geographically located at different places but operate in a coordinated way. Therefore, virtual microgrids are seen as a single controlled entity from the main grid point of view, although to be coherent with the microgrid concept, the virtual microgrid must be able to operate in islanded mode or coordinated multiple islands, which is so unlikely so far.
It is important to mention that the power systems in the future will contain, apart from microgrids, multiple types of new entities and emerging concepts in the framework of decentralized energy supply systems, such as Smart Power Cells or Power Hubs (Hinker *et al.*, 2018). In this way, it can be said that one of the main characteristics of a microgrid is its capacity of operation in both grid-connected and islanded modes, which bring about part of its most attractive benefits.

2.2.2. Overview of a microgrid configuration

Microgrids as active distribution networks can describe a wide range of case-depending configurations and topologies. However, a typical radial-based configuration is shown in Figure **2-3** based on Chowdhury *et al.* (2009) description.
The depicted microgrid assembles a set of distributed generation sources, storage systems and loads and it is interconnected with the main grid through the so called point of common coupling (PCC). The connection can be through an MV or LV distribution network. The DERs are normally close to the loads and are provided with power electronic interfaces to favor control, metering and protection functions during both operation modes (Chowdhury *et al.*, 2009).
Every single DER is equipped with a microsource local control system (MC) while the microgrid has a central control (CC) that interacts with every single controller. The main function of the MC is to individually control the power flow and voltage profile accordingly to the demand in normal operation or under contingencies. The MCs are also in charge of the participation in economic scheduling, load tracking and demand-side management.

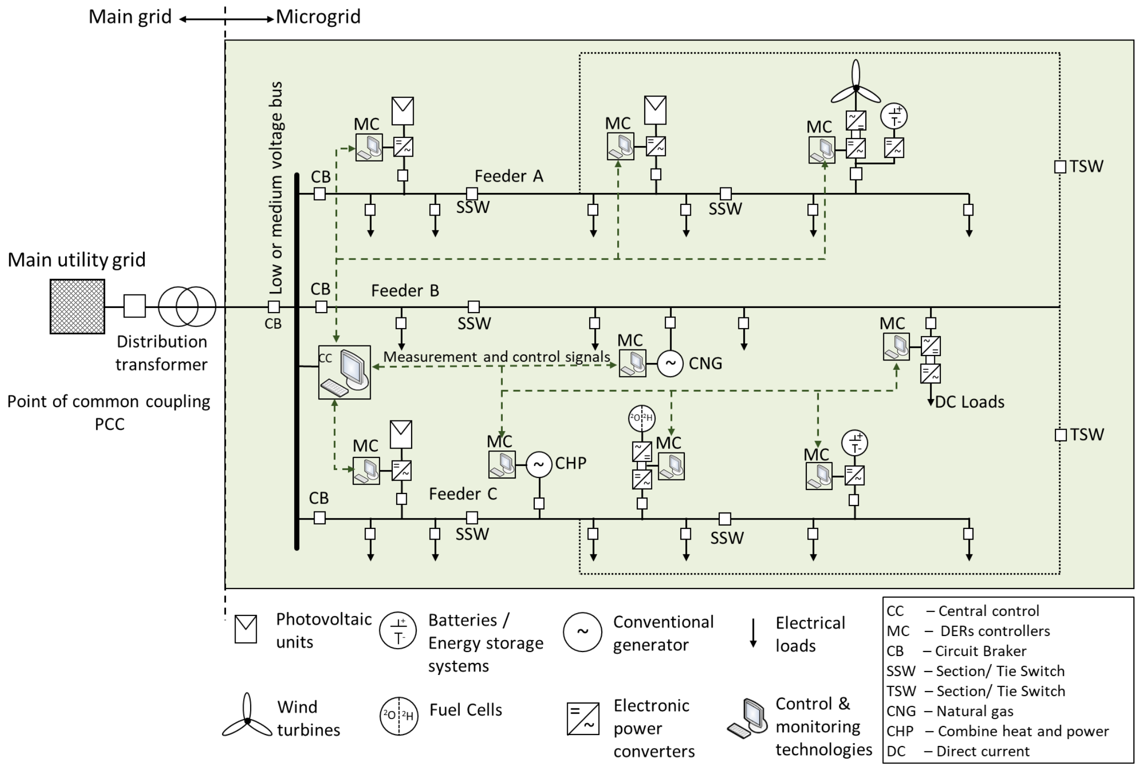

Figure 2-3.: An example of a typical microgrid configuration, adapted from Chowdhury *et al.* (2009)

Chowdhury *et al.* (2009) describe that the most relevant visible feature of MCs is its fast response to the locally monitored voltages and currents in the MC's neighborhood.

The CC of the microgrid is in charge of the complete control and protection of the microgrid employing the individual MCs. Thus, the CC receives measurements and device statuses from the different MCs, ensures energy optimization for the microgrid, determines the power dispatch and voltage set points for all the MCs during the next period to guarantee voltage and frequency levels at loads, and perform protection coordination. The CC is provided then with two main functional modules: Energy Management Module (EMM) and Protection Co-ordination Module (PCM) (Chowdhury *et al.*, 2009).

The MCs handle primary frequency-voltage control, while the microgrid CC system addresses the frequency and/or voltage secondary and tertiary controls of the microgrid (Farhangi and Joos, 2019). Martin-Martínez *et al.* (2016) describe the stability control levels in the microgrid as it is shown in Figure **2-4**.

The DGs in the microgrid can be DC sources such as solar PV units, fuel cells and ESS, or AC sources like microturbines and wind turbines. The interconnection of the first DC-type DGs sources needs the utilization of DC-to-AC power converter interfaces (inverters). While the AC-type DGs can be interconnected either directly (conventional generators) or through

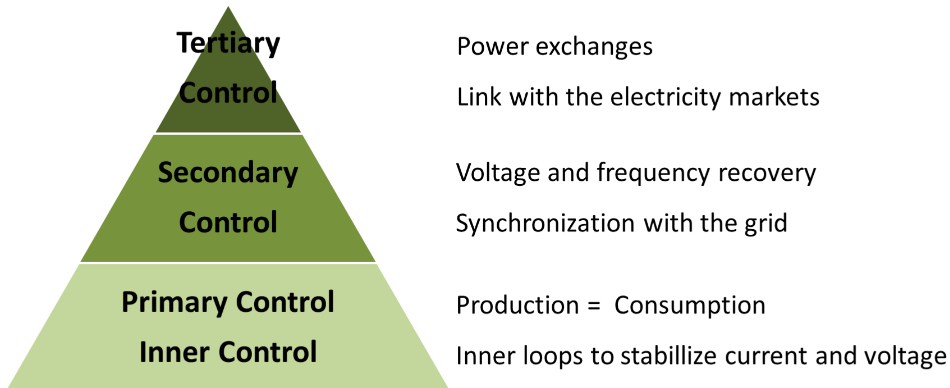

Figure 2-4.: Control levels responsibilities, adapted from Martin-Martínez *et al.* (2016)

the use of AC-to-AC power converters (variable speed generators such as wind turbines or high-speed microturbines) to guarantee the voltage and frequency operation between limits.

Considering the type of DER and its power-electronic-based interface, the DERs units in the microgrid are normally categorized into two groups: grid-forming (dominant) and grid-following (smaller units) (Farhangi and Joos, 2019; Jayaweera, 2016). The grid-forming units are mainly planned to regulate the voltage of the system, for which, the central control defines reference set-points to get the required voltage profile. For that reason, the DGs act as voltage sources and slack terminals. Grid-following units are intended to accomplish the generation and demand balance through the injection of power into the microgrid through their governed active- and reactive-power set-points by the CC. For both units categories, MC ensures a set-points tracking regardless of the disturbances and changes in the microgrid.

Normally only dispatchable DGs with fast response and suitable capacities can take the duty as grid-forming units. On the contrary, non-dispatchable DGs will take role of grid-following, which would conduct power injection within the microgrid. In some cases, the small units are treated as negative loads (Jayaweera, 2016). Typical types and use of grid-forming and grid-following units are shown in Table **2-1**.

The use of electronic power systems architectures are very case-depending, and it is still a wide relevant research topic. However, for tackling the planning problem in the microgrids, the integration of DERs in the microgrids is mostly influenced by the dispatchable and non-dispatchable nature of the generation units, Figure **2-5**. For example, dispatchable generation can be controlled with a high level of flexibility to operate and respond in real-time to fulfill the requirements of the system in terms of demand and stability. On the contrary, non-dispatchable energy sources such as the renewable wind, solar, or run-of-river micro-hydropower generation, cannot be controlled by operators with the same level of flexibility since their output power depends on non-controllable primary energy.

It is important to mention that dispatchable and controllable capacities are necessary to guarantee the system's operation. For example, dispatchable DGs are necessary to follow

Table 2-1.: Typical technologies of grid-forming and grid-following DGs

Types of DGs	Technologies	Directly coupled	Converter coupled
Grid-Forming DGs	Gas-turbine generators and CHPs	✓	✓
	Diesel generators		✓
	Energy storage systems		✓
Grid-Following DGs	Wind turbines	✓	✓
	Solar PV units		✓
	Fuel cell		✓

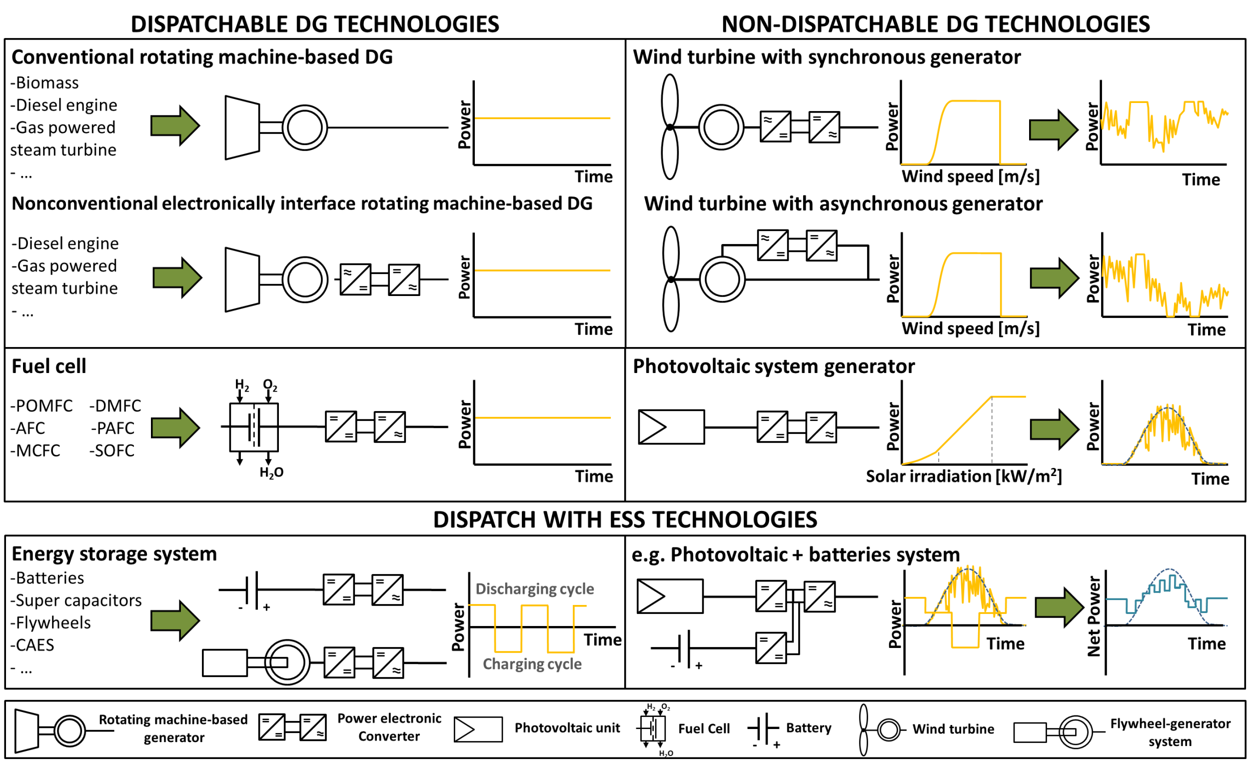

Figure 2-5.: Overview of different examples for dispatchable and non-dispatchable technologies

load demand and balance system's mismatch power, provide spinning reserve, facilitate economic generation dispatch, manage grid congestion, among others. Therefore, the output power can be considered constant under normal operation conditions, i.e., the left side of Figure 2-5. On the contrary, non-dispatchable generation has normally a stochastic and intermittent operation behavior that leads to variations in the output power, i.e., the right side of Figure **2-5**. These uncontrollable changes in the generation of power are transferred into the grid and can cause unbalances and frequency instability problems. Consequently, wind- and solar-based renewable generation, for example, require a flexible dispatchable source of power to compensate for their intermittent power generation.

In the last decades, ESS in microgrids have become affordable as technologies that introduce flexibility in electric systems. As a result, novel distributed ESS in LV microgrids and utility-scale centralized ESS in MV utility microgrids have become suitable solutions for compensating and smoothing the intermittent operation of wind and solar generation, as seen in the bottom part of Figure **2-5**. Therefore, different types of energy storage technologies have become part of the microgrid's configuration, and their technology and storage principles have been chosen depending on different criteria and application, Table **2-2**.

Table 2-2.: ESS and their suitable application, adapted from CIGRE WG C6.22 (2015a)

Application	Hydro	CAES	Batteries							Flywheel	SC
			Na/S	Na/NiCl	Li/ion	Ni/Cd	Ni/MH	Pb/acido	Redox		
Time-shift	○	○	○	○	◍	◍	◍	○	○	●	●
Renewable integration	○	◍	○	○	○	○	○	○	○	◍	●
Network investment deferral	○	◍	○	○	○	◍	◍	◍	○	●	●
Primary regulation	○	◍	○	○	○	○	○	○	○	◍	●
Secondary regulation	○	◍	○	○	○	○	○	○	○	●	●
Tertiary regulation	○	○	○	○	○	◍	◍	○	○	●	●
Power system Start-up	○	○	○	○	○	○	○	○	◍	●	●
Voltage support	◍	◍	○	○	○	○	○	○	◍	○	○
Power quality	●	●	◍	●	◍	◍	●	◍	◍	○	○

○ System suitable ◍ System less suitable ● System not suitable

CAES: Compressed-air energy storage, Na/S: Sodium–sulfur, Na/NiCl: Sodium-tetrachloroaluminate, Li/ion: lithium-ion, Ni/Cd: Nickel–cadmium, Ni/MH: Nickel–metal hydride, Pb/acido: Lead–acid, Redox: flow battery, SC: Super-capacitors

It is worth noting that batteries have become a very convenient and accessible technology, whose applicability has increased due to the continuous improvements in capacity, efficiency, and commercialization costs. Consequently, batteries have allowed active management of intermittent and renewable energy generation, as well as serving load during islanded operation.

Loads are classified widely as critical and non-critical loads. The aim is to prioritize the operation regarding their relevance and functions. For example, a planning methodology may consider only the critical loads to size the DERs. Under this consideration, DERs and a part of the non-critical loads must be planned and designed under a load-shedding by way of either automatic under-frequency or under-voltage scheme (Farhangi and Joos, 2019). Moreover, loads that contribute to microgrid's demand management strategies can be connected (and controlled) using either a conventional circuit breaker or AC-to-AC power electronic interface to allow more flexible control.

Additionally, microgrids can be equipped with both section switches (SSW) (or sectionalizing circuit breakers), which are normally closed, to partition the distribution system and tie-switches (TSW), which are normally open, to change the configuration of the microgrid as an operation management strategy in normal and emergency operation conditions (Thakar *et al.*, 2019). The optimal location of SSW and TSW is a current matter of research, and their use has been mostly intended to enhance the microgrid's reliability through its topology modification (Elsaiah *et al.*, 2016; Gazijahani and Salehi, 2018b).

Microgrids would have two main aims depending on their operation mode. In a grid-connected mode, the microgrid management system would combine the costumers in order to interact with the wholesale markets. In islanded mode, the microgrid management system would try to regulate the energy and economic flows of the microgrid using for instance a local market. In every case, the microgrid's control and management system would try to guarantee the stability and security of the network in real-time (Martin-Martínez *et al.*, 2016).

Therefore, microgrid requires complex control, management, and supervisory systems together with specific protection, automation, communication, and remote monitoring systems to ensure safe, reliable, efficient, and autonomous operation at all times and operation modes (CIGRE WG C6.22, 2015a). The technologies, control actions, protection schemes, automation strategies, etc., are a complex and extensive research topic that comprise particular engineering problems mainly aimed at solving the day-to-day microgrid's operation issues and most of them do not influence the power resources and topology planning stages. Therefore, detailed concepts and theory behind this are left out of the scope of this dissertation, and only specific operational characteristics of the microgrid are taken into account in the proposed methodologies. These characteristics are considered and explained in further chapters.

2.3. Microgrid stakeholders, commercial and regulatory frameworks

The implementation of microgrids in actual scenarios requires to acknowledge that the current structure of most of the power systems around the world is based on electric markets where electricity is treated as a commodity that can be bought, sold, and traded, and have in most cases a mixed private-public infrastructure and assets for that purpose. Therefore, microgrid deployment is under these commercial and regulatory frameworks. This is the reason why, it must be considered from the planning stage.

Different stakeholders or actors will be involved in the planning and operation of microgrids, and CIGRE WG C6.22 (2015a) arguments that the optimal operation of the microgrid will depend on the objectives of relevant actors, especially the microgrid's ownerships, and commercial and regulatory frameworks that rule the value and requirements for the provision of services by the microgrids. Therefore, commercial and regulatory conditions should seem attractive to investors based on value revenues from the provision of different services. For example, in principle, different microgrid's impacts could be sold as services, depending on the needs of local stakeholders (CIGRE WG C6.22, 2015a), but this point will be addressed in the following sections.

2.3.1. Stakeholders in the microgrids

A stakeholder is defined as a person or group of people (organizations, corporations, or systems) who has an investment, share, or interest in something as a business or industry, in this case, the microgrid. In the same direction, the stakeholders will be affected by the microgrid's impacts. CIGRE WG C6.22 (2015a) describes possible stakeholders with a direct financial interest and direct or indirect benefits from the microgrid installation and operation. They are presented in Table **2-3**.

Table 2-3.: Stakeholders in the microgrid, adapted from CIGRE WG C6.22 (2015a)

Stakeholders in the Microgrid			
	Actor's name	**Actor's type**	**Description**
Owner of the microgrid	Independent power producer (IPP)	People or corporations	Customer or consortium of customers that owns and operates (DGO) the microgrid and its DERs
	Distribution network operator (DSO/DNO)	Corporation	The entity is also responsible for the operation of the grid at the distribution level.
	Utility supplier	Corporation	Utility-owned case
Direct and indirect beneficiaries	End-use microgrid customers	People or corporations	Residential, commercial, or industrial loads within the microgrid.
	Grid customers	People or corporations	Loads outside of the microgrid
	Utilities or Bulk Energy Suppliers	System	The entities outside the microgrid that supply power to the grid
	Society	People, Corporations, and Other Entities	Everyone who could be affected by microgrid's impacts.

According to Li *et al.* (2017), future research in the planning of ADNs should consider different perspectives of multi-stakeholders. Therefore, the diverse and sometimes conflicting planning goals of different stakeholders should be taken into account.

Three microgrid ownership models have been identified and are presented by CIGRE WG C6.22 (2015a): ownership by the DSO/DNO, ownership by a customer or consortium of customers, and independent ownership. Depending on the owner, certain benefits could attract more attention and be prioritized at the operation and/or planning optimization. For example, the utility-owner case might have a stronger interest in the technical benefits than a customer-owner case, where the economic interest might be their priority (CIGRE WG C6.22, 2015a; Li *et al.*, 2017). For instance investor-owned utility companies (e.g. PG&E in the USA) are interested in investing mostly in grid infrastructure and receiving a guaranteed rate of return on those investments at the same time that contributes to the improvements of the distribution network system performance and capacity.

At this point it is important to highlight that Distributed Network Operators (DNO) are companies traditionally in charge of distributing electricity under the conventional unidirectional passive distribution model. Therefore, due to the transition into ADNs, the classic DNO is being transformed to adopt the responsibilities of the called Distributed System Operators (DSO). The DNO term originated as a European acronym for regulated network operators conducting business under the European unbundling scheme (Boyd, 2017; McDonald *et al.*, 2017). The term "DSO", on the other hand, is itself slowly spreading from Europe to the USA. Companies that operate the distribution network and sell electrical energy to the consumers by themselves through retailers in the USA are known as Distribution Companies (DISCOs) (Munoz-Delgado *et al.*, 2019).

Actors at the transmission level in Europe are aggregated as Transmission System Operators (TSO) (Edmunds *et al.*, 2017), while in the US the TSO have been separated into Independent System Operators (ISO) and Regional System Operators (RSO) to move towards an unbundled structure and competition in the electricity market (Kury, 2013; Granderson, 2019). RTOs normally have the same functions as ISOs but cover a larger geographic area. Furthermore, in the USA, there are other actors such as traditional generating companies (GENCO) or now distributed generation companies (DGENCO), as well as independent DSOs (IDSO) (Munoz-Delgado *et al.*, 2019).

The microgrid's investments and operations will depend on the current type of market with different financial incentives in place or future emerging "free-market" or "fully liberalized market" models. Therefore, the benefits to the stakeholders will result from an economic dispatch of microgrid assets based on market price signals that for instance, could cause the microgrid to import less power in times of high demand, or supply AS depending on the upstream requirements and bids (CIGRE WG C6.22, 2015a). However, the evolution and future restructuring of the electricity markets are still an extensive research problem that might require comprehensive microgrid planning methodologies for their design and analysis.

2.3.2. Economic and regulatory framework

It is important to understand two main aspects of the economic and regulatory framework where the proposed planning methodologies can be applied: microgrids can be planned under either a traditional or a fully liberalized commercial and power regulatory scenario (CIGRE WG C6.22, 2015a):

- **Traditional:** In this scenario, customers purchase electricity from retailers and the export of power to the main grid is compensated by regulated tariffs. Therefore, microgrid owners may have and operate DERs but cannot access markets to prevent competition with liberalized actors. The installation of renewable DERs is relatively small and it is mostly motivated through Feed-in-Tariffs (CIGRE WG C6.22, 2015a). This is currently the most common scenario for the deployment of microgrids, where microgrids with higher generation capacity and participation in markets, such as utility microgrids, might be more attractive based on value revenues and the business case (CIGRE WG C6.22, 2015a; Stadler *et al.*, 2016).

- **Fully liberalized:** In this case, microgrid owners with small DERs can access markets directly and participate in the wholesale energy and power system service markets. These are achieved normally through aggregators, coalitions, cooperatives, etc., and the grid fees are based on capacity bases (CIGRE WG C6.22, 2015a). This scenario also opens the barriers for local energy markets where intra-microgrid energy trading is possible.

It should be mentioned that although the detailed description and features of a DSO or DISCO company variate among regions or countries, in principle both of them can participate in the markets since they normally own and operates a part of the entire distribution network (Ghadi *et al.*, 2019), while customer microgrids cannot trade directly in the wholesales market as it is explained by Ghadi *et al.* (2019). This structure of data, information and power exchange among actors is explained below.

Links among actors in a restructured power market with microgrids.

Ghadi *et al.* (2019) offer a view of the links among a DSO/DISCO and microgrids in a TSO/ISO-supervised restructured power market, which is based on the model of the active distribution networks as a “system of systems” proposed by Kargarian Marvasti *et al.* (2014). This framework for the interactions of several connected microgrids are modeled to maximize the benefit of each implicated entity as DSO/DISCOs and microgrids are considered as individual agents that exchange information and electricity under a hierarchical optimization procedure. In Figure **2-6**, the framework is expanded to consider possible utility microgrids as part of the whole framework.

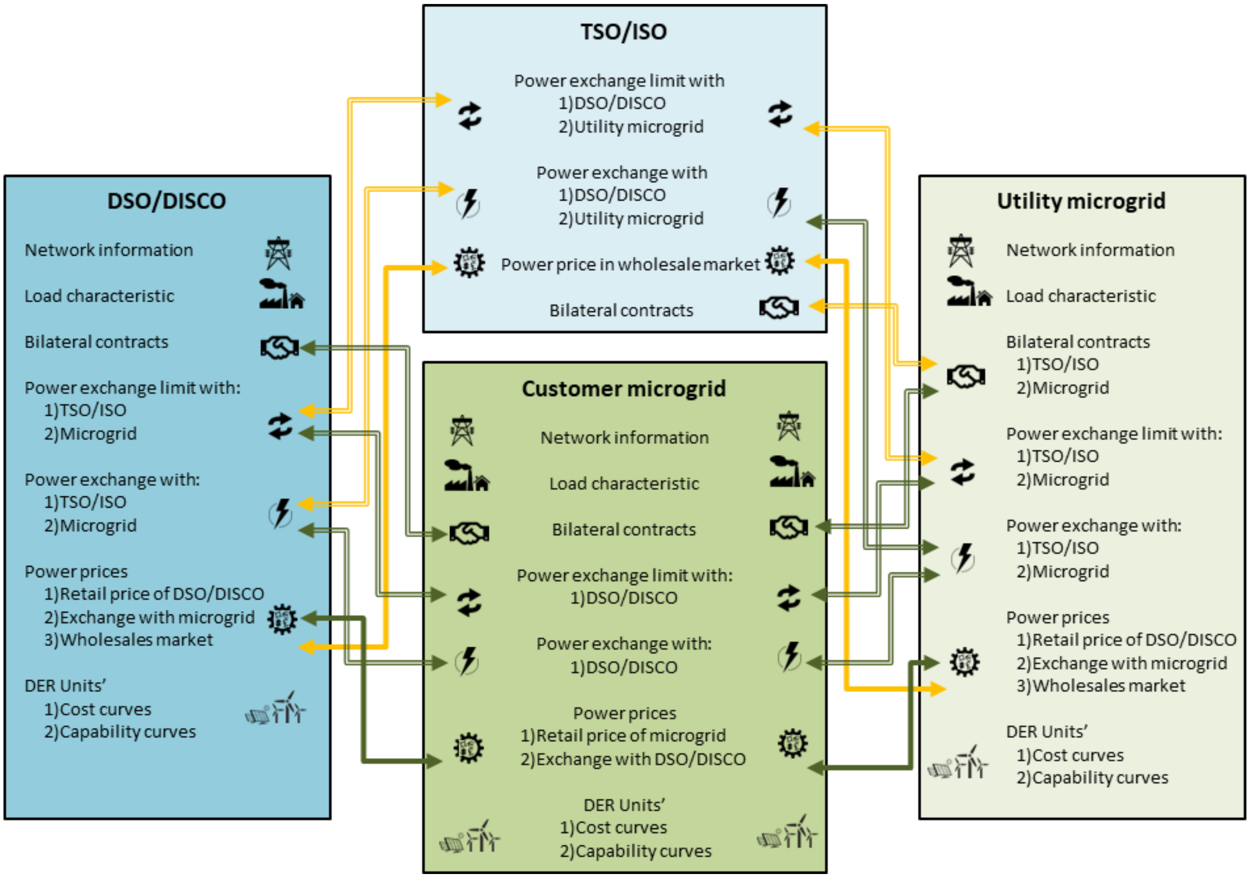

Figure 2-6.: Links among actors in a restructured power market with microgrids, adapted from Ghadi *et al.* (2019)

Four main agents are involved in the operation of a distribution network in a restructured power market (Figure **2-6**). The actors include a customer microgrid, utility microgrid own and operated by a DSO/DISCO, DSO/DISCO, and TSO/ISO. From this perspective, Ghadi *et al.* (2019) describe the operation of the distribution network in two different periods between the DSO/DISCO and the microgrid.

The first period occurs when the DSO/DISCO gets from the TSO/ISO operational and market data such as the energy clearing price of wholesale market or limits for power exchange with the upstream grid. The DSO/DISCO manages in a local process the data exchange with the microgrid. Hence, operational and market parameters of the distribution network are established based on information such as the bilateral contracts and energy price for energy trade with the microgrid, and the required information is transferred as signals to the microgrid. In the case of a utility microgrid, the DSO/DISCO would have complete control of the DERs that will allow direct response to the market signals from the TSO/ISO based on their capacity or trade with other microgrids to optimally respond to the system requirements.

In the second period, the data sent from the DSO/DISCO is processed in the microgrid and the information on bilateral contracts and power exchange is returned to the DSO/DISCO or another microgrid, for example the utility microgrid. Ghadi *et al.* (2019) highlight that other information regarding loads, network and generation units is not shared with other agents, and only until local marginal prices for particular buses and microgrids are cleared and transactions between DSO/DISCO and microgrids are closed, power exchange and technical conditions are transferred to the upstream agents.
It is important to highlight that despite utility companies or DSOs are potential investors of future microgrid resources[1], the scenario is are still rear (Hirsch *et al.*, 2018), and only a few examples of utility microgrid exist in the world (See Appendix C). Therefore, the structure of data and information exchange among the TSO/ISOs, DSO/DISCOs and microgrids owned by DSO/DISCOs, utility companies, independent power producers or customers require further research and will strongly depend on the achievements in the restructuration of current electric markets.

2.4. Benefits and impacts of the microgrid implementation

The potential effects of the installation of a microgrid (impacts), the arising consequences of its implementation and operation (costs and benefits), and who will be involved by the microgrid (stakeholders), must be identified during a planning/design stage to justify the institution of a microgrid (Farhangi and Joos, 2019; CIGRE WG C6.22, 2015a). In this direction, the concept of microgrid has arisen together with a wide range of potential advantages that can be offered to the power systems. For example, since the first publications about the microgrid concept, potential benefits and impacts related to a massive and extensive integration of DERs into the current power systems have been highlighted. For example, the microgrid concept has offered a complete approach to remove directly some problems with the DER's integration (Lasseter *et al.*, 2002), and hence it might be said that one main goal of microgrids is to integrate and facilitate all advantages of non-conventional and renewable low-carbon generation technologies, several storage devices and high-efficiency systems such as CHP (Chowdhury *et al.*, 2009, Chapter 2-3).
In consequence, the main benefits and impacts of the microgrids come from the introduction of flexibility in the power systems operation. For example, microgrids can be seen from the main grid as self-controlled entities that can operate as a single aggregated flexible load, but at the same time as a source of power or ancillary services (AS) (Lasseter *et al.*, 2002). Therefore, potential benefits for the main grid would be congestion relief, postponement of investments on new generation capacity, response to load changes and local voltage support. Additionally, microgrids are planned to mainly meet the local needs, whereby customers (or

[1] Hirsch *et al.* (2018) refer to the European Union project "More Microgrids" where a DSO is identified as potential microgrid ownership. In this case, the DSO owns the distribution system and is responsible for retail sales of electricity to the end customers.

owners) benefit with an uninterruptible power provision, improvement of the local reliability, reduction in the feeder losses, and the support of the local voltages (Lasseter *et al.*, 2002). The benefits and impacts of the microgrid are even being expanded nowadays to more complex concepts such as the networked microgrids (Alam *et al.*, 2019), where the previously mentioned advantages are maintained.

The CIGRÉ working group C6.22 "Microgrids evolution roadmap" presented in 2015 the technical report "Microgrids 1 Engineering, Economics, & Experience" (CIGRE WG C6.22, 2015a). The technical report addresses the main required aspects to justify, develop and implement viable microgrids, proposing clear microgrid design objectives/benefits and elements for the creation and evaluation of a business case for the implementations of microgrids (CIGRE WG C6.22, 2015b). In such a way, it is suggested to differentiate the concepts of "benefits" and "impacts". Therefore, following the approach in (CIGRE WG C6.22, 2015a), "impacts" are defined as the different alterations that arise from the installation and operation of a microgrid in the systems where it belongs: electrical system, economic system, or environmental system. "Benefits" are defined as the actual economic earnings and effects from positive impacts that the microgrid can return to the stakeholders. CIGRE WG C6.22 (2015a) claims that all impacts must be translated into benefits based on the categories and types listed in Table **2-4**.

2.5. Challenges for a massive microgrid deployment: a planning and value streams problem

Complex engineering problems must be tackled to achieve a widespread deployment of microgrids within the current power distribution systems. Most relevant barriers and potential difficulties are described in this section under the microgrid's planning problem perspective (Lopes *et al.*, 2013; Chowdhury *et al.*, 2009, ,Chapter 1).

(1) High investment costs and economic justification:

The required additional DERs and general complexity of the microgrids lead to an abrupt increase in investment costs. This barrier especially affects the cost-benefit framework for microgrid's deployment feasibility. Hence, this disadvantage for the microgrid development should be tackled and studied under techno-economic analysis in the first instance from the planning stage (Farhangi and Joos, 2019, Chapter 1). For example, microgrids can facilitate additional value streams compared with traditional distribution networks that must be considered from planning to improve the economic viability of microgrid installation. The microgrid's key value streams are outlined by Stadler *et al.* (2016) as:

- Participation in Demand Response programs.
- Export of power electricity back to the main grid.

Table 2-4.: List of prominent benefits due to the installation of a microgrid, adapted from CIGRE WG C6.22 (2015a).

Category	**Type of benefit**	**Relevant impacts**	**Description**
Economic benefits	Reduction of the purchased electricity from the grid	Amount of purchased energy, more participants and prices in markets	The total purchased energy from the grid is reduced since the structure of the microgrid allows the supply of energy from internal DERs.
	Deferral in the infrastructure investment	Rate of load growth	The microgrid and internal DERs contribute to reduce the peak grid loading, which lead to defer certain distribution network investment/upgrade costs . This offers value to the DNO through the present value of money not spent
		Planned investments in infrastructure	
		Peak current in the equipment	
Technical benefits	Ancillary Services (AS) provision	Contracted AS use	Potential AS such as spinning and non-Spinning reserves, voltage and frequency regulation, and black start support can be provided by the microgrid, to improve local PQR
		Contracted AS value	
	Improvement of Power Quality and Reliability (PQR)	Reduction in the expected outage frequency, duration, times, and Non-Delivered Energy (NDE)	Microgrids can reduce outages to critical loads within the microgrid by disconnecting from the megagrid in the event of a fault (islanding), and by disconnecting dispatchable or controllable loads, when it is applicable. In certain cases, they can also provide emergency power outside the microgrid to supplement reduced grid supply during a contingency. This can benefit both microgrid customers as well as customers outside the microgrid.
		Value of customers' power reliability	
Environmental benefits	Reduction of greenhouse gases and general emissions	Emissions rates of each source	The inclusion of renewable DGs in the microgrid can allow energy generation with significantly lower emission of greenhouse gasses and other pollutants as compared to regular generation rates
		Cost of emissions	
		Fuel consumed from each source	

- Cost reductions due to added resiliency against outages and lost loads.
- Participation in local energy markets.

Microgrids are self-controlled entities with possibility of participating in demand response programs (Farhangi and Joos, 2019; Stadler *et al.*, 2016). For example, load curtailment actions such as peak shaving, or energy consumption shifting among periods of time can be used to decrease energy consumption. This actions can be achieved by varying end-users' loads directly with strategies such as load shedding, or by increasing or decreasing the microgrid's inside electricity production from DERs (Stadler *et al.*, 2016). Stadler *et al.* (2016) identify two types of currently available demand response programs: Incentive or Event-Based (or Dispatchable) program, and Price-based programs (Non-Dispatchable). **Ancillary services (AS)**, for example, are considered part of event-based programs, where customers are compensated for reducing their electric loads upon request, or for giving to the program's operator some level of control over the user's electric equipment. In every case, (Stadler *et al.*, 2016) claim that microgrids might be planned to consider the participation in such programs.

As part of the demand response program participation, one of the most discussed and highlighted sources of revenue is the sale and **export of power** to the main utility grid from the on-site generation in the microgrid. Kwasinski *et al.* (2016, Chapter 3) explain the techno-economic assessment for justifying the investment in different types of DERs to maximizing the value revenues from power exporting. Authors claim this is a complex task whose results based on grid parity concepts depend on the time horizon, the comparison of costs against the type of market of the utility grid (from day-ahead markets to the spot market), and the used method for determining the value of excess power generation in a microgrid. In this way, there are different types of markets where the microgrids might be installed, some examples are retail market, wholesale market and spot markets.

Another value stream for dealing with the high cost of expanding microgrid's concept use is the increased value due to **added reliability and resilience** to prolonged outages. For example, critical loads such as hospitals, military facilities, industrial facilities, laboratories, research centers or water treatment plants may be planned with high levels of redundancy based on advanced backup and emergency generation systems, which lead to a complex definition of the economic criteria from the planning stage of such systems (Stadler *et al.*, 2016). Therefore, microgrid comprehends coordinated on-site generation and storage resources that can be properly sized and located from planning to be used in normal and emergency operation. For that purpose, DERs' capacity can be optimally sized over the capacity for normal and continuous operation duty, in order to meet critical and in most cases complete microgrid's demand during outage periods or unintentional islanded operation (Stadler *et al.*, 2016). However, considering this type of value revenue is not an easy task that is still a hot research topic.

Participation in local energy markets is another identified value stream source for supporting a massive microgrid deployment. This value stream is explained by Stadler *et al.* (2016) as the microgrid's possibility of trading energy not only with the main utility grid but also with neighboring microgrids or other ADNs. However, this source of the value stream is still not well established, since it requires a special local energy market framework, which is an emerging topic, and research is currently in a relatively early stage (Stadler *et al.*, 2016). Consequently, this potential value revenue will play an important role in the future with the emergence of local energy markets, and its potential will require the proper DERs allocation planning for maximizing the reserve power of the microgrids.

In conclusion, the optimal techno-economic decision making for the investment in microgrids concepts is closely linked with the allocation of DERs in the microgrid to optimally enhance the value stream in the microgrid. Hence, this challenge leads to the necessity of having available proper planning methodologies.

An extensive theory behind electric markets and the role of microgrids as part of them in future can be found in (Kwasinski *et al.*, 2016, Chapter 3; Chowdhury *et al.*, 2009, Chapter 9-10), while general economic principles for the electric power system planning and theory of power system economics can be consulted in (Seifi and Sepasian, 2011, Chapter 3; Kirschen and Strbac, 2004), respectively.

(2) Technical challenges

Extensive research on features and functionalities of the most used component technologies in microgrids has been conducted and well documented in the last decades. In this way, major technical challenges for a wide deployment of microgrids are related to the operation and control of multiple DERs in the microgrid as well as the design of the microgrid's protection system (Lopes *et al.*, 2013; CIGRE WG C6.22, 2015a). For example, Lopes *et al.* (2013) and Chowdhury *et al.* (2009, Chapter 1) claim that the main technical barriers for the implementation of microgrids are associated with the relative lack of technical knowledge to coordinately control and operate several DERs inside a microgrid. This situation is likely one of the main reasons for a higher amount of research in microgrid's operation, protection and communication areas instead of the microgrid's planning problem.

Nonetheless, the intermittent operation of renewable technologies are still prominent technical issues from planning perspective (Ghadi *et al.*, 2019). For example, uncertainty in the output power generation of renewable DGs can lead to an inappropriate location and size of the microgrid's DERs from the planning stage, which could bring about high power losses, voltage instability, and power quality and protection degradation in the power distribution networks (Ehsan and Yang, 2019), and represent a barrier for the extensive deployment of microgrids considering current planning tools.

Therefore, although the operation and control challenges are relevant for a massive microgrid deployment, these topics are out of the scope of this doctoral research as long as they do not impact directly the results in the microgrid planning stage. Contrary, uncertainties in renewable generation and load demand are studied as part of the planning methodologies in this doctoral research.

Deeper information about microgrid's operation can be found in literature (Farhangi and Joos, 2019, Chapters 5-7,9; Kwasinski *et al.*, 2016, Chapter 8; Chowdhury *et al.*, 2009, Chapters 4-7), or late review papers in operation and control (Pourbehzadi *et al.*, 2019; Sahoo *et al.*, 2018).

(3) Lack of standards

Despite global policymaker and authorities have encouraged international standardization committees and organizations to include as part of their agendas the preparation and production of standards for smart grid, ADNs and microgrids applications, it is important to point out that not all aspects related to the implementation of microgrids and their particular features have been totally covered (Kwasinski *et al.*, 2016, Section 9.2). This lack of standardization and strong microgrid's case-dependency constitutes an important obstacle to the massive deployment of microgrids.

However, different organizations have proposed and published different standards, application guides, technical brochures, etc., that can apply to particular steps in the design, integration and operation of a microgrid. A summary of the main standards is presented in Figure **2-7**

It is important to mention that for this doctoral research, the IEEE Std 1547 has a representative role since this standard describes the requirements that DERs needs to have a connection to a main grid in the USA (IEEE Standard Association, 2018). Furthermore, although the standard is not focused on the microgrid concept, the IEEE Std 1547.4 is the "IEEE Guide for Design, Operation, and Integration of Distributed Resources Island Systems with Electric Power Systems", which offers information about the possible intentional and unintentional islanding of the network. The IEEE Std 1547-2003 was under revision at the moment of this research (Boemer *et al.*, 2018) and a reviewed version was released in June 2018 and was approved for its adoption in the USA on February 12, 2020. Other publications relevant for this research are the CIGRE technical brochure from the working force groups WG C6.22 and WG C6.19.

(4) Administrative and legal issues

Despite the worldwide efforts for encouraging the integration of carbon-neutral renewable DG technologies, there is, in general, an absence of legislation and regulations for the integration and operation of microsources in many countries (Lopes *et al.*, 2013; Chowdhury *et al.*, 2009). This is called by Hirsch *et al.* (2018) the challenge of the "legal and regulatory uncertainty", which can be analyzed from two key legal questions:

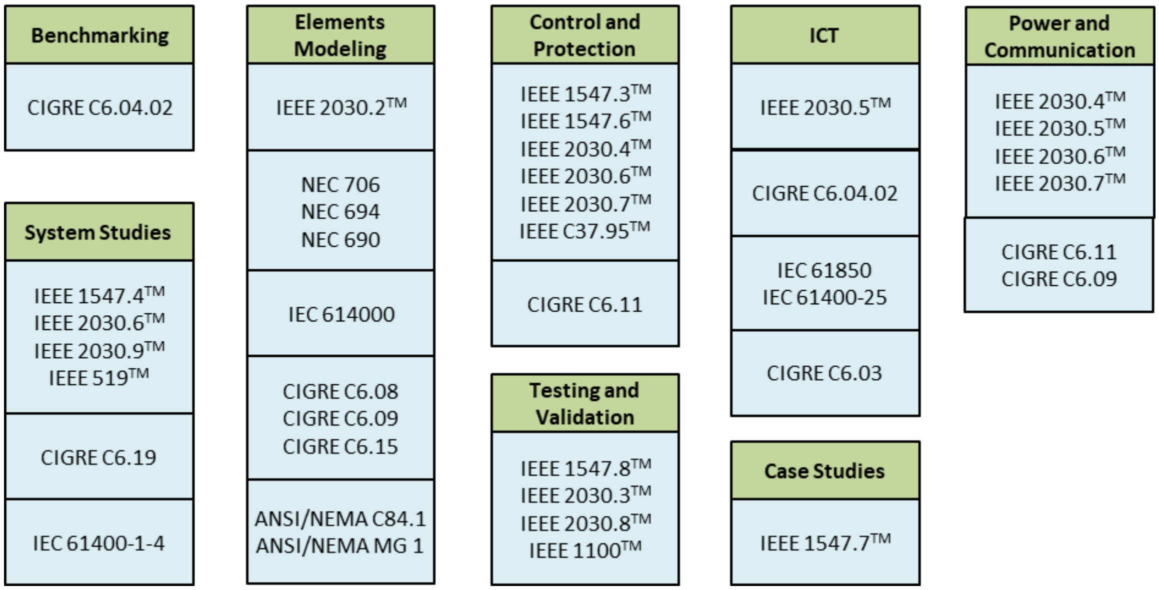

Figure 2-7.: Standards and application guides relevant for the design of microgrids, adapted from Farhangi and Joos (2019); Kwasinski *et al.* (2016); CIGRE WG C6.22 (2015a)

- First, are microgrids planned to become electrical distribution utilities and consequently be supervised and regulated by state agencies?.
- Second, if the microgrids are relieved from the state regulation as utility companies, do they suit to current legal frameworks ruling electricity trading and permissions/licenses for the generation and distribution of electricity?

Hirsch *et al.* (2018) claim that these two key questions may lead to contradictions. For example, the situation where microgrids are entities with the qualification of electric utility companies might have implications for other agents in the distribution system. In this case, the license for using public infrastructure will hardly depend on the already existence of an electric utility with an exclusive franchise over the assets. However, in the second case, although several electric markets currently comprise companies (the Independent Power Producers) as actors, under the current administrative and legal frameworks microgrids may not fit completely into any of the currently defined market participants (Hirsch *et al.*, 2018).

The situations described before may lead to a certain opposition to a massive deployment of microgrids from actors such as existing electric utilities (Hirsch *et al.*, 2018). The main reason for this reluctance is the possible revenue decrease for existing utilities due to the self-generation and consumption of electricity within microgrids and investment deferral impact(See Section 2.4) that might reduce the revenue from payments due to investments in infrastructure by the utility company. Therefore, Hirsch *et al.* (2018) claim that a possible strategy to stimulate the active participation of utilities into the transition process into ADN with microgrids is through changing from a cost of service paradigm into a performance-based approach. In this way, the utility would get additional revenues from investments in microgrid infrastructure, improving efficiency, enhancing reliability, etc., instead of only the revenues for selling as much as energy per hour.

As a conclusion, it is clear that different administrative, legal, and regulatory solutions must be established in future to encourage the deployment of microgrids at the same time as current actors are benefiting from the positive microgrid's impacts. From that point, it could be envisioned that the role of the existing and future electric utility companies and DSOs/DISCOs will have a representative role for a massive deployment of the microgrids, and microgrid planning methodologies will have to expand their application fields in this type of stackeholders.

2.6. A thesis on future microgrid planning methodologies from current deployment challenges

As it was seen in previous sections, the microgrid concept has been presented as a powerful solution where two types of microgrid and potential owners can be distinguished: utility microgrid and customer microgrid. However, it was also found that the potential benefits of installing a microgrid are mainly attributed in literature to the microgrid without special distinctions among the different types of microgrids (CIGRE WG C6.22, 2015a). Contrary, the challenges for microgrid deployment involve not only the general microgrid concept but also lead the attention to particular barriers depending on the owners and types of microgrid. Therefore, it could be claimed that these obstacles must be properly addressed from ground stages in the microgrids development roadmap to optimally achieve after the potential benefits of a massive deployment of microgrids.

Initial stages in the development of the microgrid concept have been already consolidated, and have brought about the current theoretical description and definitions of the concept. This knowledge, together with the parallel research and development on DER technologies, control architectures, communication protocols, etc., has given rise to test-bed and pilot projects around the world. However, the current status is still far from granting conditions for a massive deployment of microgrids. Conversely, a certain reluctance to the concept implementation has remained, or it has even increased in some circles or regions.

Inferring from circumstances, current and future research on microgrids must aim to find effective solutions to mitigate the high investment costs and improve the required economic justification, include and deal with inevitable technical issues, update existing and generate new standards, and formulate clear administrative and legal frameworks for the deployment of microgrids. Consequently, the planning stage could be seen as a key stage for removing those barriers for the deployment of microgrids.

With this cue for the planning engineering, several research questions have been formulated and solved already in the literature. However, many proposals have been addressed from the chasing of benefits and solutions to technical issues, while the disadvantages of the concept have been omitted at a certain level. As a consequence, microgrids have been treated from planning as a concept where benefits normally impact multiple stakeholders and can be achieve indistinctly of the type of the microgrid. For example, considering benefits it could be relatively obvious that future microgrid planning methodologies must include multiple objectives to maximize as many benefits as possible, and prioritize economic objectives considering the high investment costs and stakeholder interests. Nevertheless, from current challenges such as administrative and legal frameworks, or economical necessity of active participation in either existing traditional or new fully liberalized electric market, it can be envisioned that microgrid planning methodologies will become very relevant at the MV level to make decisions for the deployment of MV utility microgrids or networked microgrids.

In this context, it can be anticipated that utilities are possibly better positioned than other agents to plan, invest and provide microgrid services to their current retail customers. For example, electric utility companies may already have infrastructure in place, expertise, administrative and legal structures, economical solvency for investing, and franchise rights from authorities to provide electricity to end-users. Furthermore, current barriers for exploiting possible microgrid value streams seem to be easier to overcome with the current capabilities of utilities or DSO companies. For instance, several authors have claimed that one of the most promising features of the microgrid will be its capacity of providing AS to the upstream grid. For that purpose, microgrids would act as third parties to provide AS when the TSO requires the services through procurement, for example.

TSO is the actor responsible for guaranteeing the operational security of its control area, and for that purpose AS are required. Hence, in a liberalized market, TSO procures AS from selected grid users that qualify for providing these services and ensures appropriate management of the resources in place to safeguard adequate AS provision capabilities. In that scheme, DSO/DISCO will have a bridging and managing role in the data and information exchange between the TSO and the microgrids in a TSO-supervised structure, as it was analyzed previously in this dissertation. Therefore, it might be possible to infer that MV microgrids such as utility microgrids, or networked microgrids, under complete control and disposition to the particular interests of the DSO or the utility, could have a more advantageous position at the moment of offering services such as AS rather than customer microgrids. For example, currently the majority of AS procurement is with electric generation companies, and existing contracts of independent power producers normally encompass limited or none obligations to provide AS. With a full liberalization of markets it is expected that independent power producers can compete in the wholesale and retail markets and can participate more actively in the AS markets. However, it is necessary to recall microgrids are entities that interconnect DERs and loads in a controlled area with well-defined boundaries, which would lead to the legal and administrative uncertainty on the utilization of current network infrastructure by potential microgrid owners, e.g. Independent power producers, as is discussed before.

Furthermore, as it was mentioned in Section 2.5, different performance-based strategies are likely established to recognize actors (e.g. electric utilities or generation companies) from their investments to enhance reliability, security, and clean generation[2]. Consequently, there are already examples of electrical utilities exploring microgrids as a strategy to provide additional services, improve reliability, and re-adapt to possible business models.

With this in mind, four key features for future microgrid planning methodologies are stated in this doctoral thesis in Table **2-5**.

Table 2-5.: Key features for future microgrid planning methodologies

1)	Future microgrid planning methodologies must comprise multiple objectives to exploit the benefits of microgrid deployment. Additionally, methodologies must be formulated to admit *a posteriori* decision making, which leads to true-multi-objective optimization models.
2)	Future microgrid planning methodologies must include potential value streams as part of the planning objectives, and AS provision has been envisioned as one of the most promising advantages of microgrids.
3)	Future microgrid planning methodologies will deal inevitably with technical issues such as uncertainty in demand and generation variables. Therefore, the methodologies must be adapted to first, consider operational issues and second, incorporate uncertainty modeling techniques.
4)	Future microgrid planning methodologies must focus during the first stages of microgrids development roadmaps on plausible and better-positioned types of microgrid, when current available legislation/regulations and envisioned restructures are considered. Hence, the planning of medium voltage utility microgrids and/or networked microgrids seems to be a central strategy for the future development of power systems and the massive deployment of microgrids.

In the next two sections, AS provision will be studied as a promissory feature in microgrid planning, and the current state of the art on microgrid planning will be analyzed based on existing achievements and drawbacks.

[2]A current example in Colombia could be an extension of the named "Cargo por confiabilidad" (Botero Duque *et al.*, 2016) to actors different to generation companies.

2.7. Provision of ancillary services and their revenue streams for microgrids

AS (Ancillary services) have been associated since very early with the most potential benefits of the microgrids (Lasseter, 2001), ideas that have been steadily reinforced along with the microgrid development roadmap. As we covered in our discussion before, future microgrid planning methodologies, such as the proposed in this dissertation, must certainly consider these types of services. Therefore, it is worth to describe with more detail the definition and general characteristics of the AS.

To offer a simple definition of the AS, the Directive 2009/72/EC of the European Parliament and the council describes them as "a service necessary for the operation of a transmission or distribution system"[3] (European Parliament and Council of the EU, 2009). In this context, system operators are not only responsible for supplying electricity to end-consumers, but also ensuring system reliability. For that purpose, electric markets[4] include a variety of AS to maintain a satisfactory level of operational security through a permanent possibility to balance supply and demand of energy (Zhou *et al.*, 2016; ACER, 2011).

The specific AS, exact definitions and requirements of each service vary among markets and regulations. Nonetheless, there is an almost completely widespread idea that AS are provided by a third party and are procured by TSOs for ensuring the operational security of the system (European Parliament and Council of the EU, 2019; Zhou *et al.*, 2016). This means that in the liberalized market, AS are contracted by TSOs from certified and chosen grid users, generators, or loads (ACER, 2011; Zhou *et al.*, 2016).

In every instance, the main AS comprises active and reactive power reserves that can be automatically or manually operated for balancing power and controlling voltage. For example, active power reserves can be required as a response of real-time load following and aiming to secure an instantaneously physical balance between generation and demand in their control areas (ACER, 2011). Thus, the first categorization of typical AS procured by TSOs to ensure system stability and security are:

- Frequency ancillary services (balance of the system)
- Non-frequency ancillary services (voltage control, black start)

[3] The Article 2(48) of Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market in electricity (recast) complemented the meaning as follow: "ancillary service means a service necessary for the operation of a transmission or distribution system, *including balancing and non-frequency ancillary services, but not including congestion management*" (European Parliament and Council of the EU, 2019).

[4] Electric markets are defined by the recast Electricity Directive as "markets for electricity, including over-the-counter markets and electricity exchanges, markets for the trading of energy, capacity, balancing and ancillary services in all timeframes, including forward, day-ahead and intraday markets." (European Parliament and Council of the EU, 2019).

Additionally, a subset of these AS is commonly procured through market-based mechanisms known as regulation, spinning, and non-spinning reserves (Zhou *et al.*, 2016).

Frequency ancillary services

1. **Regulation and frequency response AS**

   The AS for balancing of the system (frequency regulation) uses regulation reserves to permanently and automatically balance the generation and demand of energy in the system from small fluctuations. For that reason, this is accomplished by maintaining a prudent level of active power AS. The responsible generation units must respond in real-time to automatic generation control signals, and the actions (output power change) take place in a time window of some seconds and not more of five minutes in most markets (Zhou *et al.*, 2016). Additionally, the regulation mechanism can be presented as a single commodity or can be separated into two types of services depending on markets.

   - Frequency up-regulation: generation capacity that is available to increase output
   - Frequency down-regulation: generation capacity that is available to decrease output

   Other markets have created a third type known as fast frequency regulation, mostly provided by ESS and demand response. These involved technologies, normally connected through power-electronic converters to the grid, can change output faster than traditional generators (Zhou *et al.*, 2016).

2. **Contingency response AS**

   The AS for providing additional generation capacity during emergency events uses contingency reserves to compensate the loss of generation or considerably increase on demand that can critically affect the power mismatch between generation and demand. The reserves are normally segmented in two categories (Zhou *et al.*, 2016):

   - Spinning or synchronized reserves: The reserve is provided by generation resources that are in service and firmly generating and have still the capacity to increase (ramp-up) or decrease (ramp-down) their output power.
   - Non-Spinning or non-synchronized reserves: The reserve is provided by generation resources that are out service and have the capacity of putting into operation within a required timeframe.

   Spinning reserves are intended to support a fast system response to outages or other contingency events, while non-spinning reserves are intended to support the system to recover or maintain from unplanned contingency events. Contingency reserves typically require response times between 10 to 30 minutes and can also be provided by the reduction of load with demand response resources.

Non-frequency ancillary services

Non-frequency AS might comprise several services that can be supplied by generation and demand response resources such as (European Parliament and Council of the EU, 2009; Zhou *et al.*, 2016):

1. Black start capabilities.
2. Reactive supply and steady-state voltage control.
3. Fast reactive current injections.
4. Inertial response for local grid stability.
5. Short-circuit current
6. Island operation capability

However, as it is claimed by Zhou *et al.* (2016), despite TSOs managing to account for adequate resources through internal requirements and other procurement mechanisms for this AS, there are not well defined existing markets to operate these services in some countries. For example, despite in Colombia there are assets for voltage control, there are no specific regulations for compensating of reactive power in the national interconnected system (Carvajal *et al.*, 2013). In fact, only until last year non-frequency AS were officially included and defined by the European Parliament and Council of the EU (2009) as "a service used by a transmission system operator or distribution system operator for steady-state voltage control, fast reactive current injections, inertia for local grid stability, short-circuit current, black start capability and island operation capability". Although it has been debated the profitability of these types of services, this is a step towards fully liberalized markets, local energy markets, and microgrids' participation. However, current market conditions lead to visualize convenient first to focus on frequency AS rather than non-frequency AS from planning purposes.
To sum up the functions of two of the main types of these AS, black start capability is maintained to provide the required input energy to start up bigger generation units and reset the system after a fault and case wide power outage (Zhou *et al.*, 2016). Regarding the reactive supply and steady-state voltage control, TSOs must also maintain the voltage levels across the buses in the systems in order to ensure secure and stable operation. To this end, an adequate level of reactive power (leading and lagging) must be provided at proper locations (normally close to the node/bus where it is required) in the transmission and distribution networks. Reactive power is currently mainly provided by generators units and transmission assets (European Commission, 2017; Glowacki, 2020).
A summary of this classification is presented in Figure **2-8**.

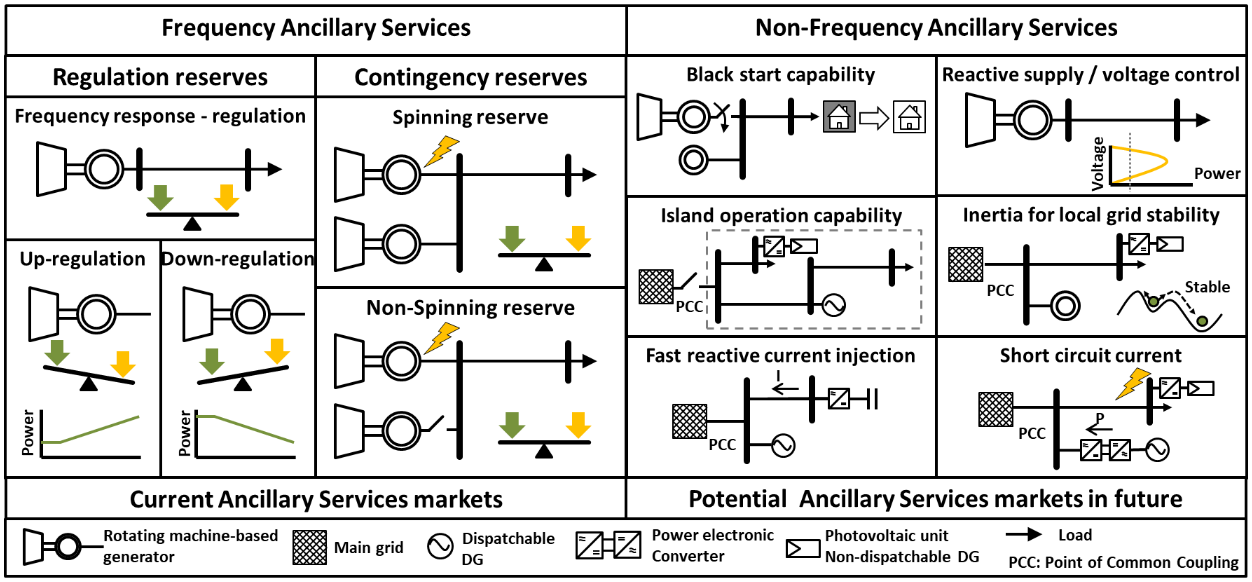

Figure 2-8.: Outlook of ancillary services in the power systems

The ancillary services market and revenue streams

The AS market variates among TSOs and regions in terms of types (or names) of procured AS, regulations/conditions and the market process. Examples of regulations are the required response time to a signal, minimum asset size, bid duration etc., while examples of the market process are bidding procedure, clearing prices definition, pricing, tariffs, etc., (Zhou *et al.*, 2016). However, most of AS markets function based on a bidding structure (Cardoso *et al.*, 2017). In that respect, 1) the TSO (market operator) request bids (offers) from assets, such as microgrid and/or other AS suppliers for the procured AS; 2) a bid from the AS provider is submitted as a signal containing the results of the system dispatch formulation for energy and AS; 3) the TSO accepts the bits, defines clearing prices for the procured AS and dispatches these assets to provide energy and AS to ensure the secure operation of the system (CIGRE WG C6.22, 2015a). Under this context, Zhou *et al.* (2016) mention that winning bids for energy and AS provision are mutually exclusive, but an asset can be compensated for both generation and AS provision in the same period.

Cardoso *et al.* (2017) and Stadler *et al.* (2016) describe the revenue streams from AS in the microgrids as a very beneficial value stream of the microgrid installation. However, the exact revenue will strongly depend on the type of market and the planning and design of the microgrid by itself, as it is concluded by Contreras *et al.* (2019) and Peñaranda *et al.* (2019). Nonetheless, microgrids are intended to participate in both energy and AS provision markets, which would represent value revenues to the microgrid's stakeholder. The state of the art regarding the application of microgrids in providing AS from planning and operational feasibility will be presented in the next section.

Despite AS markets are constantly changing, deeper explanation and examples of the main theory of the AS markets can be found in (Kirschen and Strbac, 2004, Chapter 5). Furthermore, Zhou *et al.* (2016) provide a very good analysis of the main markets in the USA and offer a solid background regarding the AS markets, procurement and provision process.

2.8. The microgrids planning problem - State of the art

As we discussed at the beginning of the Chapter, the microgrid concept was presented in literature since the beginning of the millennium by Lasseter (2001) and Marnay *et al.* (2001). However, literature regarding the constitutive components and technology required by the concept has been discussed for several years before[5] (e.g Kueffner (1986)) from the development and use of alternative DGs. Afterward, the convergence of information, communication, automation, metering, and diverse technological innovations and the power system engineering gave rise to the name of Smart Grids (Farhangi and Joos, 2019), and ADN with the integration of DERs in the traditional passive distribution networks (Chowdhury *et al.*, 2009, Chapter 1).
In this context, research in microgrids has increased substantially in the last two decades. For example, a cursory examination[6] of this trend is shown in Figure **2-9**. The figure shows how the use of the "microgrid" term in the title of specialized publications has exponentially increased over other general terms associated with the current energy transition. As we discussed before, there has been a bigger amount of research on operation and design topics rather than planning topics, and the purpose of this section is to present the most representative research on methodologies and strategies for the microgrids planning, and the optimization techniques and consideration of the AS as part of the research.

2.8.1. A review of the planning methodologies on microgrids and other active local area power and energy systems

Research on microgrid planning has increased in last years. However, there are other local area power and energy system that share characteristics with microgrids and a considerable percentage of the research on planning have also been concentrated on them, for example, ADNs. For that reason, this review of the state of the art considered also them.
In the first place, authors have presented very exhaustive literature reviews on the planning topic, identification of current issues and future research requirements and trends. The most

[5]It is not possible to track an exact moment. However, most sources and authors refer to the 1970s oil and energy crisis due to substantial petroleum shortages and prices rocketing. As a consequence, many sectors started discussing solutions and technologies that led to the current change in the energy use paradigm and transition era (U.S. Energy Information Administration, 2020).

[6]We are aware of the lack of accuracy in the numbers regarding the pertinence of the publications with these basic search equations.

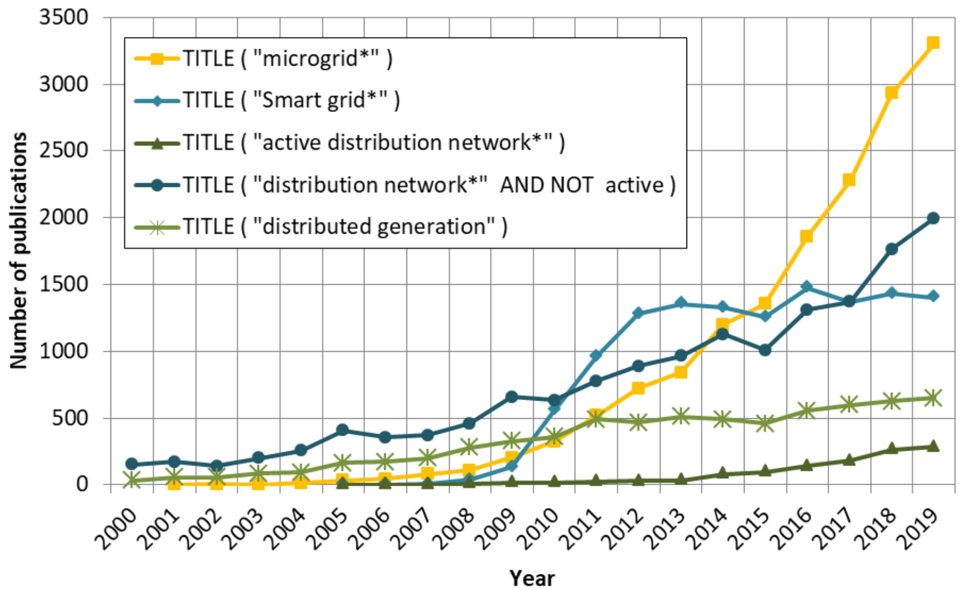

Figure 2-9.: Overview of the number of publications with key energy transition terms used the titles (source www.scopus.com)

representatives review papers are listed in Table 2-6.

The combination of the listed papers in Table 2-6 offers a comprehensive overview of the current state of the art in the planning of microgrids and similar local area power systems. It is noticeable that most of them cover requirements for the formulation of the optimization problem (objective functions, decision variables, constraint functions), modeling of uncertainties, solving tools (e.g metaheuristic optimization algorithms, multi-criteria decision-making techniques), the necessity of incorporating operation into the planning stage, review and analysis of potential actors and current market conditions, and brief descriptions of the available system's architectures and generation and storage technologies.

For example, Ghadi *et al.* (2019) present an updated review paper where planning issues and challenges of ADNs and microgrids are analyzed from a review of the state of the art. Authors claim and support on literature that the next step in the energy transition is to decentralize ADNs based on microgrids. Authors tackle planning form operation issues based on electric market characteristics. Furthermore, they analyze the literature to consider networked microgrids as part of the future decentralization of ADNs. We found that this is the first paper that focused on the review of papers based on the particular problem of planning microgrids from the ADN concept. Other publications tackle the problem from the ADN concept. For instance, Li *et al.* (2017) show clear challenges and requirements for the optimal planning of ADN, including microgrids. Authors highlight the necessity of considering multiple objectives, multiple stakeholders, uncertainty and including the operation into the planning stage and suggest based on literature the bi-level optimization technique as a po-

Table 2-6.: List of main review papers on planning of microgrids and other ADN

Author(s) / Year	Document title
Resent advancements and challenges for planning	
Ghadi *et al.* (2019)	From active distribution systems to decentralized microgrids: A review on regulations and planning approaches based on operational factors
Li *et al.* (2017)	A review of optimal planning active distribution system: Models, methods, and future researches
Saboori *et al.* (2017)	Energy storage planning in electric power distribution networks – A state-of-the-art review
Kazmi *et al.* (2017b)	Smart Distribution Networks: A Review of Modern Distribution Concepts from a Planning Perspective
Xiang *et al.* (2016)	Optimal Active Distribution Network Planning: A Review
Georgilakis and Hatziargyriou (2015)	A review of power distribution planning in the modern power systems era: Models, methods and future research
Uncertainty modelling techniques for planning	
Ehsan and Yang (2019)	State-of-the-art techniques for modelling of uncertainties in active distribution network planning: A review
Optimization problem and techniques for planning	
Anderson and Suryanarayanan (2019)	Review of Energy Management and Planning of Islanded Microgrids
Verma *et al.* (2019)	A Review on Optimization Methodologies for Distribution Network Expansion Planning
Agarwal and Jain (2019)	Distributed Energy Resources and Supportive Methodologies for their Optimal Planning under Modern Distribution Network: a Review
Emad *et al.* (2019)	Computational Methods for Optimal Planning of Hybrid Renewable Microgrids: A Comprehensive Review and Challenges
Ehsan and Yang (2018)	Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques
Kazmi *et al.* (2017a)	Multi-Objective Planning Techniques in Distribution Networks: A Composite Review
Gamarra and Guerrero (2015)	Computational optimization techniques applied to microgrids planning: A review

tential strategy to tackle the problem. These same key features in the planning of ADN were highlighted and properly described by Xiang *et al.* (2016). However, the reviews on these two publications bring special attention to the general concept of the ADN. The interesting fact is that this trend has stayed in the last year, with reviews such as (Georgilakis and Hatziargyriou, 2015), where some of these aforementioned points were already identified and highlighted.

Saboori *et al.* (2017) review literature regarding the ESS as part of the planning of modern distribution networks. Authors show various models, methods, and considerations that have been proposed to enhance the functionality of the ESS as part of the optimal planning process, where conclusions showed the strategies for the optimal ESS bus location, power rating, and energy capacity determination. Ehsan and Yang (2019) present an exhaustive review, discussion and explanation of the used and main uncertainty modeling techniques for the planning of ADN. They categorize the techniques in probabilistic techniques, stochastic optimization, robust optimization, possibilistic techniques, hybrid probabilistic–possibilistic techniques and information gap decision theory. Authors show that there is no existing single best uncertainty modeling technique so far, and the selection of a suitable technique depends on the type of uncertainty and planning problem. The review also highlights that ADN planning problems include the distributed generation investment planning, optimal storage allocation, reliability assessment, probabilistic optimal power flow, optimal reactive power planning, substation expansion and feeder reconfiguration. The review of the used techniques was also supported by the review in (Aien *et al.*, 2016) on uncertainty modeling techniques in power system studies.

Existing review literature shows direct or indirectly the relevance of the optimization problem model for the planning problem and the required solving techniques. One example is the number of review papers that have focused on the optimization techniques and formulation of the problem, compared with the review papers on the uncertainty modeling techniques, or other particular issues such as services provision by microgrids. For instance, Anderson and Suryanarayanan (2019) offer an extensive survey of the optimization models for the management and planning of islanded microgrids. One of the main contributions is the updated collection of optimization objectives, constraints, control variables, forecasting techniques, socio-economic factors, and multi-criteria decision making this paper a reference for future research. Authors identify, from 120 papers, 16 possible objective functions, 14 constraints, and 13 decision variables between optimization for operation and planning. However, the authors combined both operation and planning optimization problems as part of their review. This compendium is complemented with the publication of Verma *et al.* (2019) and Agarwal and Jain (2019), who present a complete list of popular techniques for optimal sizing and sitting of the DG, as well as software modeling and simulation tools. Emad *et al.* (2019) review optimization methodologies for the power distribution network expansion planning and one of the main contributions is the summary of optimization model characteristics from uncertainties, objectives, constraints, and used (meta-) heuristics techniques, and analyzes the methodologies from shortcomings for future research.

In conclusion, these last reviews, together with the reviews in (Ehsan and Yang, 2018; Kazmi *et al.*, 2017b; Gamarra and Guerrero, 2015) support the following points that are tackled by this doctoral research:

1. The microgrid's topology planning has not been amply considered in the literature and a holistic approach with other conventional planning goals (e.g. sizing and placing of DERs) is hardly found.

2. Although AS have been identified as potential value revenue for microgrids, the research has not given special attention to the planning stage.

3. Most of the planning methodologies have focused on the microgrid without clear consideration of the possible types of microgrids or stakeholders. Only recent research by Ghadi *et al.* (2019) showed the potential of certain types of microgrids from planning.

4. There is clear evidence on the trend for adopting mainly multi-objective approaches for solving the planning problem. However, true-multi-objective approaches have been more widely considered only recently.

5. One effective and increasingly used strategy to model multi-objective optimization problems is by metaheuristic optimization techniques.

6. Population-based algorithms as the NSGAII have been effectively tested in several previous research for the planning of power systems.

7. There is a lack of research on the decision-making strategies for the selection of a single solution in multi-objective approaches for the microgrids planning problem.

8. Literature review supports our conclusion regarding the likely use for the first time of the MOEA/D algorithm for solving the microgrids planning problems, while literature has shown the suitable performance of the algorithm for solving more than two objective functions in multi-objective optimization problems (Rodriguez *et al.*, 2020).

9. Uncertainty in the planning problem is still an open research topic due to the high case-dependency for the deployment of microgrids. In any case, authors in literature agree on its relevance and mandatory consideration despite the selection of the technique will depend on the case study conclusion.

Additionally to this large amount of publications that review and analyze the microgrid's planning problem, the publications listed in Table **2-7** were identified as key references for the particular goals in this doctoral research.
An overview of the literature in Table **2-7** shows an interesting increase in the proposed strategies during the last years to tackle the microgrids planning problem considering uncertainties, multiple objectives, included topology characteristics and/or the capacity of providing AS. These publications also show an evolution from a remarkable bigger focus on the multiple objectives issues, as in the proposal of Zidan *et al.* (2013), followed by topics such as uncertainties modeling with the proposals of Khodaei *et al.* (2015), the incorporation of AS in the planning as in (Cardoso *et al.*, 2017; Andreotti *et al.*, 2018), the development of strategies for the topology planning as in (Camacho-Gómez *et al.*, 2019; Gazijahani and Salehi, 2018b; Jiménez-Fernández *et al.*, 2018) and lately the planning of potential types of microgrids such as the Networked Microgrids with (Gazijahani and Salehi, 2017, 2018a) and novel concepts such as reconfigurable networked microgrids with (Cao *et al.*, 2020). Therefore, it might be relevant to mention that our publications have been presented to the academic community in parallel to the research in Table **2-7** or in some cases pioneering in the topic with novel proposals as we will analyze below.
Starting from the oldest proposals that in certain vein worked as reference and motivation for this Doctor research, Zidan *et al.* (2013) propose for the first-time a multi-objective distribution network planning problem with a probabilistic-based DGs model. The authors show

Table 2-7.: State of the art on probabilistic and multi-objective microgrids planning methodologies

Author(s) / Year	Document title
Cao *et al.* (2020)	A Risk-Averse Conic Model for Networked Microgrids Planning with Reconfiguration and Reorganizations
Machado *et al.* (2019)	Probabilistic and multi-objective approach for planning of microgrids under uncertainty: a distributed architecture proposal
Camacho-Gómez *et al.* (2019)	Optimal design of Microgrid's network topology and location of the distributed renewable energy resources using the Harmony Search algorithm
Gazijahani and Salehi (2018b)	Robust Design of Microgrids With Reconfigurable Topology Under Severe Uncertainty
Gazijahani and Salehi (2018a)	Optimal Bilevel Model for Stochastic Risk-Based Planning of Microgrids under Uncertainty
Andreotti *et al.* (2018)	Decision Theory Criteria for the Planning of Distributed Energy Storage Systems in the Presence of Uncertainties
Jiménez-Fernández *et al.* (2018)	Optimal Microgrid Topology Design and Siting of Distributed Generation Sources Using a Multi-Objective Substrate Layer Coral Reefs Optimization Algorithm
Celli *et al.* (2018)	Multi-Criteria Analysis for decision making applied to active distribution network planning
Cardoso *et al.* (2017)	The impact of ancillary services in optimal DER investment decisions
Che *et al.* (2017b)	Optimal Planning of Loop-Based Microgrid Topology
Che *et al.* (2017a)	Optimal Interconnection Planning of Community Microgrids With Renewable Energy Sources
Gazijahani and Salehi (2017)	Stochastic multi-objective framework for optimal dynamic planning of interconnected microgrids
Guo *et al.* (2016)	Multi-objective optimal planning of the stand-alone microgrid system based on different benefit subjects
Khodaei *et al.* (2015)	Microgrid Planning Under Uncertainty
Guo *et al.* (2014)	Multi-objective stochastic optimal planning method for stand-alone microgrid system
Arefifar and Mohamed (2014b)	Probabilistic Optimal Reactive Power Planning in Distribution Systems With Renewable Resources in Grid-Connected and Islanded Modes
Pereira Junior *et al.* (2014)	Multiobjective multistage distribution system planning using tabu search
Zidan *et al.* (2013)	Long-term multi-objective distribution network planning by DG allocation and feeders' reconfiguration

the relevance of a multi-objective problem for the distribution network planning and claim that this should be solved with a true-multi-objective optimization algorithm. The authors tested the methods on a 38-bus balanced test system and a 119-bus balanced test system and uses the population-based metaheuristic NSGA-II as a multi-objective optimization algorithm for a 20 years study. Hence, results support the effectiveness of the methodology, although the ESS effect, particularly islanded mode operation in microgrids, and an AS capability are not contemplated in that work. As another proposal, Pereira Junior *et al.* (2014) formulate the planning problem as a multi-objective dynamic mixed-integer non-linear programming problem and solved by means of the multi-objective tabu search algorithm that is a trajectory-based metaheuristic. Authors propose the optimization of the costs (investment and operational) and reliability in order to optimally upgrade and reconfigure the distribution network (substations, lines, trajectories, sectionalizing switches and tie lines). The proposal is tested in a 54-bus system and the results support the necessity of a multi-objective approach and the effectiveness of metaheuristics for solving these type of planning problems. However, this proposal was presented for a totally passive distribution network, where the potential of a proper topology planning was demonstrated.

Arefifar and Mohamed (2014b) present a proposal for the optimal allocation of reactive resources in a distribution network with a capability for grid-connected and islanded operation. One of the main contributions is the probabilistic modeling of uncertainties, and the planning problem is formulated with two objective functions to reduce the annual energy losses of the grid-connected system and increase a proposed microgrid success index. However, the main drawback of the methodology is the solution of the model through a virtual mono-objective optimization problem. Guo *et al.* (2016, 2014) present a multi-objective stochastic chance-constrained programming model for the planning of stand-alone microgrids. In the first one, the net present cost in the life cycle and pollutant emissions are minimized. In the second one, the generation cost for distribution companies is minimized and an internal return rate for DG owners is maximized. However, despite both works highlight the advantages of a multi-objective strategy, the research is limited to stand-alone operation, and the AS are not considered as part of the planning problem. Moreover, a decision-making strategy over the Pareto-front to choose the optimal microgrid design from the outcome is not implemented either which is a missed characteristic in most of the multi-objective proposals. Nonetheless, the proposal of Arefifar and Mohamed (2014b) is relevant since some of their models were implemented by Contreras *et al.* (2018).

Celli *et al.* (2018) highlight the challenge for the decision-maker of the planning problem considering the multiple conflicting criteria. The authors propose a systematic approach for project selection based on muti-criteria analysis in case of a large set of planning alternatives, as with the multi-objective approaches. The strategy is tested for the selection of a planning alternative from a set of possible rural remote microgrid planning solutions based on the allocation of ESS, and uses Analytic Hierarchy Process (AHP) for the decision making process. The authors conclude that the comparison of alternatives is a complex task due to the normal number of alternatives and evaluation criteria. Results show the effectiveness of the AHP strategy for identifying the planning alternative that best satisfies the stakeholders' decision criteria.

Although Arefifar and Mohamed (2014b) modeled the uncertainty through probabilistic techniques, the other authors neglected the effect of the stochastic nature of renewable technologies in the planning. Thus, one important proposal to tackle planning with a strong focus on the effect of uncertainties was presented by Khodaei *et al.* (2015). Authors propose for the first time a model for planning of microgrids with uncertainty in the physical (load, variable renewable generation) and financial (market prices) information and implement a robust optimization approach. The microgrid planning problem is solved in two components, one investment master problem and one operation sub-problem. The results showed the effectiveness of the proposed model, although it is important to highlight that robust optimization is based on the optimization of the limits of the worst-case conditions and normally maintains a conservative tendency (Ehsan and Yang, 2019; Aien *et al.*, 2016). In this sense, other proposals have been implemented with stochastic scenarios based or probabilistic uncertainty modeling techniques.

One of the first authors to analyze and include the topology effect in the planning of microgrids was Che *et al.* (2017b). They propose a methodology for the optimal planning of loop-based microgrids based on graph partitioning technique and integer linear programming optimization method. Authors demonstrate the advantages of a loop-based over a traditional radial-based topology. However, the methodology presents drawbacks in the strategy that may lead to sub-optimal microgrid topology designs. Additionally, in this proposal the size and location of DERs are predetermined. Shortcomings in this methodology are identified and enhanced by Cortes, Contreras and Shahidehpour (2018), which is part of this doctoral research. The strategy identifies loop-based microgrid topology design limitations and defines optimal loops by discarding unfeasible and non-optimal structures in an active distribution network.

Two papers in 2017 presented planning strategies considering the possibility of clustering for the definition of networked microgrids. In (Che *et al.*, 2017a), an optimal planning methodology of community microgrids is presented. The authors propose a clustering-based method for the optimal planning of networked microgrids by applying a probabilistic minimal cut-set iterative method for optimal planning of the interconnection system based on the optimal reliability. Results show the effectiveness of the methodology to find interconnection alternatives for microgrid cluster-based topologies at the same time that the advantages of community microgrids are demonstrated. However, in this proposal DERs are predefined and uncertainties neglected. The second publication is (Gazijahani and Salehi, 2017), where a well-developed strategy to consider uncertainties for the planning of interconnected microgrids is proposed. The authors present a stochastic multi-objective framework for the minimization of two cost functions. The proposal considers uncertainty from economic, technical, reliability, and environmental variables and the optimization is formulated for the optimal allocation of DERs and section switches. Scenarios based stochastic technique and backward scenario reduction technique are used to model uncertainties. The methodology is formulated as a multi-objective optimization problem for the minimization of two cost functions for the economic cost evaluation (e.g. investment, operation and maintenance) and reliability cost evaluation, and it is solved through a multi-objective particle swarm optimization algorithm. Numerical results show the performance of the algorithm and demonstrate that clustering conventional distribution systems into some interconnected microgrids will improve the technical characteristics of the system, confirming the conclusions by Che *et al.* (2017b).

Additionally, Gazijahani and Salehi (2018a) propose a stochastic risk-based bi-level model for optimal planning of microgrids considering uncertainty. For that purpose, the authors propose two different levels of risk from planning called risk-neutral and risk-averse strategies to include operation features into the planning stage. The upper level of the optimization considers the optimal planning of DERs and the lower level the optimal switch allocation problem for partitioning distribution networks into Microgrids. Authors implement Cuckoo Search optimization and imperialist competitive algorithm for solving the upper and lower optimization levels, respectively. The strategy is tested in the PG&E 69-bus and demonstrate the benefits of the methodology. In a similar planning strategy, Gazijahani and Salehi (2018b) test a robust optimization approach for considering cases where there is a lack of full information or historical data for the uncertainty variable as in (Khodaei *et al.*, 2015). In this case a single cost function is minimized. The bi-level robust optimization problem is reduced into a single level through duality gap theory for the optimization of the robust uncertain variables and a profit-based objective function. The problem is solved through a metaheuristic called Gray Wolf optimization algorithm and the numerical results are obtained on the IEEE 30-bus test system. Results show the advantages of the proposed strategies and tackle effectively relevant points in microgrid planning, as particular cases regarding uncertainty. The proposals by Gazijahani and Salehi (2018b,a, 2017) can be considered as a very relevant reference for the future of planning methodologies. However, significant issues for an attractive implementation of microgrid remain unattended, such as revenues from supplying AS, market trading participation and a capable continuous islanded operation. Furthermore, new strategies for optimal networked microgrids clustering and topology planning for new or expansion projects in a holistic way offers plentiful research opportunities (Contreras *et al.*, 2020b).

Recently other authors have also proposed strategies for planning microgrids. Camacho-Gómez *et al.* (2019) and Jiménez-Fernández *et al.* (2018) test two novel optimization algorithms to solve the topology design and DERs placement problem under a multi-objective approach. The proposals describe an effective strategy to solve the joint optimization problem. For example, Jiménez-Fernández *et al.* (2018) propose a strategy for DERs allocation and topology definition based on the binary connection or disconnection of candidate lines for the minimization of the lines deployment cost and energy losses in the system. The optimization problem is solved by means of a very novel metaheuristic optimization algorithm called " Multi-objective Substrate Layers Coral Reefs Optimization algorithm" and compared with the NSGAII and Multi-objective Harmony Search algorithms. Camacho-Gómez *et al.* (2019) propose the solution of the same multi-objective planning problem but in this case to analyze the performance of the Harmony Search optimization algorithm. For that purpose, authors test the algorithm in the traditional mono-objective and evaluated multi-objective formulations. Results contributed to support a multi-objective approach. Notwithstanding, relevant issues in the microgrids planning such as uncertainties, time-depended energy storage systems, islanded operation, and operational aspects are not considered in both studies (Jiménez-Fernández *et al.*, 2018; Camacho-Gómez *et al.*, 2019).

Machado *et al.* (2019) propose an interesting strategy and architecture for the planning of microgrids in order to include operation into the planning stage. The planning considers the size of DERs to attend the necessities of stakeholders. The planning architecture proposes with five correlated stages called microgrid coordination, microgrid operation optimization, reliability assessment, contingency assessment and searching mechanism. Accordingly, planning is solved based on a so-called multi-attribute decision system that will provide a list of possible configurations. These possible solutions are found with particle swarm optimization technique. In other words, the strategy decomposes the microgrid planning problem into smaller subproblems. Furthermore, the present work proposes a collection of appropriate tools for each subproblem that is solved with suitable techniques such as Petri net (PN) model of microgrid coordination, the second stage uses the MILP approach to optimize the power generation scheduling, reliability indexes are found with Monte Carlo simulation, for the contingency assessment the probability of a contingency state is calculated, and the final stage executes an iterative searching mechanism with particle swarm optimization to find the candidates optimizing CO_2 emissions and profit cost. The strategy is tested for the DERs sizing in a campus microgrid and is compared with the results of a well-known tool called DER-CAM. This is a very novel strategy that can be explored in future research and expanded to further necessities such as the services provision and other microgrids structures such as networked microgrids.

In the latest research, Cao *et al.* (2020) propose a very complex strategy for the planning of reconfigurable microgrids enhancing traditional configuration strategy through the concept of dynamic microgrids. In that sense, microgrid's boundaries are not planed for static conditions but for dynamic conditions to allow reconfiguration. A risk-averse two-stage mixed-integer conic program model is used to support the networked microgrid planning. The microgrid capacity expansion and seasonal reconfiguration decisions are made in the first stage, and are validated under stochastic islanding scenarios in the second one. Authors claim that the microgrids in the ADN can be reconfigured and reorganized periodically, and they test the strategy for a seasonal period. The methodology is tested on a 33 and 56 bus networked microgrid and shows cost savings compared with traditional configuration strategies with fixed boundaries, allowing the microgrids capacity expansion with higher cost-efficiency and system performance. This novel approach can be considered for future research where other characteristics of the microgrids are evaluated from the planning stage, such as services from microgrids.

In fact, it is evident that different well elaborated proposals and very novel strategies have been proposed in the last years in parallel with the execution of this doctoral research. However, few of them have considered services and particularly AS as part of the planning methodology. One approach was proposed by Andreotti *et al.* (2018), who implement a methodology for planning distributed ESS to reduce the energy cost and provide AS to the main network. In this case, the AS is provided for the voltage regulation capacity. The allocation (size and location) problem is managed with three decision theory criteria for the minimization of the expected costs, a weighted regret felt by the decision-maker, and a stability area criterion. Therefore, different alternatives (futures) are associated with different levels of load demand and power generation by DGs along the planning horizon. Results show that an effective allocation of distributed ESS leads to reducing the costs for energy provision and supplying technical support to the grid.

However, the main publication can be the one by Cardoso *et al.* (2017), where authors include the value stream from the AS to expand the Distributed Energy Resources Customer Adoption Model (DER-CAM). DER-CAM is a well known and uses MIlP-based tool for the decision making of DERs in the planning of microgrids and ADN. DER-CAM is a mathematical model developed to determine different types and capacities of distributed energy resources inside of a microgrid and find the optimal dispatch of them. Cardoso *et al.* (2017) develop a very elaborated mathematical model to include the revenue stream from AS such as up- and down-regulation, spinning reserve and non-spinning reserve AS in the decision-making tool. Stochastic models are used to model uncertainty in the planning and a single-objective profit cost function is optimized employing deterministic MILP tools. The modifications in the DER-CAM are tested in a single building and multi-building microgrid for the CAISO and PJM market territories in the USA. The numerical results suggest that the participation of Microgrids in the AS markets can affect the optimal sizing of resources as well as their dispatch of energy. For example, the campus microgrid of the Illinois Institute of Technology in the USA was developed with the use of DER-CAM and it can be a practical example of an AS supplier. However this model is based on a mono-objective cost function with a deterministic technique, which has been found as a drawback because there always exists more than one contradictory objective function in the planning problem that cannot be accurately modeled *a priori* (Contreras *et al.*, 2019).

To sum up, in the last five years different proposals for solving the microgrid planning problem have been proposed simultaneously while this doctoral research has been developed. These strategies have proven in some cases individually and in other more comprehensively the key points that were identified as key features for the future microgrids planning methodologies. All the proposals above have been properly presented and some of them can be considered as solid references for future research and comparative points for the POMMP and POMMP2 methodologies proposed in this doctoral thesis. Other proposed strategies are an open door for future research questions and expansion toward the requirements for effective and massive deployment of microgrids.

2.8.2. A review of the ancillary service supply by microgrids

As we have shown, there is no existing extensive research where the AS are considered from the planning of microgrids. However, a bigger amount of authors have research from the technical feasibility of providing these types of services from microgrids. In this direction, Yuen and Oudalov (2007) present for the first time an assessment of the technical feasibility of microgrids to supply AS. Gomes and Saraiva (2010) present two optimization models to allocate reactive power/voltage control, active loss balancing and demand interruption by microgrid agents. Madureira and Peças Lopes (2012) propose an AS market framework for voltage control in a system with multiple microgrids, which authors call the VAR market. Lee *et al.* (2016) display also AS for voltage control by using ESS in microgrids. For that purpose, power electronic-based converters are considered for the active and reactive power control and voltage and frequency droop control. Results show that ESS can be used to reduce voltage fluctuations on the microgrid. Majzoobi and Khodaei (2017) developed and presented a microgrid optimal scheduling model to support the microgrid's capability of providing AS to the utility grid, and mainly localized AS. The scheduling strategy is modeled for load variations including hourly ramping, 10-min based load following, and 1-min based frequency regulation. A final example could be (Husein and Chung, 2018). The authors develop a microgrid planning model to simulate the optimal operation of the microgrid and calculate the system cash flow. This model was used to design a campus microgrid.

This short reviewed research demonstrates and highlights the potential of microgrids in the provision of AS, but they do not completely tackle the technical considerations from the perspective of microgrid planning (Contreras *et al.*, 2019).

3. Microgrid mathematical models for the probabilistic multi-objective planning problem

A solution to the planning problem is an output from the decision-making process, which is accomplished over a set of optimal alternatives from the multi-objective planning optimization problem. For that purpose, a planning methodology requires an array of high-level mathematical models that composes the main topic of this Chapter. To visualize a planning solution process, the planning problem can be divided into three global stages (Ehsan and Yang, 2019):

1) Modeling stage
2) Strategy stage
3) Optimization/decision-making stage

We adapt the three stages approach for the solution of the planning problem with a crosswise microgrid planning methodology. This means that the proposed POMMP and POMMP2 methodologies in this doctoral thesis are formulated to systematically couple and employ the outputs of each stage for ultimately solving the planning problem. The three stage strategy is aligned with the “microgrid benefit quantification methodology” proposed by CIGRE WG C6.22 (2015a) and “microgrid design process” proposed by Farhangi and Joos (2019), whose approaches start with the selection and definition of a microgrid base case (called the “microgrid benchmark compilation” by Farhangi and Joos (2019)) and microgrid element modeling. This starting point can be understood from the strong microgrid’s case-dependency for their design and planning contexts, which is as a condition considered in the POMMP and POMMP2 methodologies. Consequently, POMMP and POMMP2 are planning methodologies for the expansion of existing microgrids or the transformation of ADN or passive distribution networks into microgrids.

The modeling and strategy stages are parallel and comprise the required mathematical models for the microgrid planning optimization problem and the strategy of the planning problem based on the planning type, the time-scale, and optimization problem definition and modeling. The optimization/decision-making belong to the solving stage, where selected

algorithms and solving tools are used to accomplish the optimization and decision-making tasks.
This chapter aims to cover the general features and adopted formulations for the microgrid mathematical modeling and their relationship with the planning type, time-scale and number of stages of the strategy stage.
As part of the research it is identified that the minimum elements that must compose a proper mathematical modeling for the microgrid planning optimization problem can be classified in five groups:

1. Mathematical model of the components.
2. Mathematical model of the distribution network.
3. Mathematical model of the uncertainties.
4. Mathematical model of the operation.
5. Mathematical model of the economic framework.

The first group comprises the required mathematical models for all the active and passive components in the microgrid such as DERs (generation, storage and active loads) and demand (loads), Section 3.1. Different types of technologies are suitable to be used in the microgrids. Thus, four of the most representative technologies in microgrids are adopted in this research: dispatchable rotational-based DG (e.g. microturbines, biomass plants, etc.), non-dispatchable renewable technologies (wind generation and solar generation), and ESS (e.g. batteries). In all cases, both direct and electronically-interface through power electronic converters are considered as grid coupling technologies under the purposes of a planning problem formulation.
The second group involves the steady-state model for the initial or existing base passive or active distribution network. The mathematical model is explained in Section 3.2 and defines the structure of the base system on which the microgrid that will be planned or added. The models contain the electrical topology and topology options in the system, peak expected demand, resource profiles and other relevant information.
The third group comprehends the mathematical model for the uncertainties in the system, Section 3.3. The selection of the modeling technique depends on the case conditions, existing information, available computational resources and level of required accuracy. However, it can be said that the access to historical data of the uncertain variable is the most decisive factor for the selection of the modeling technique (Aien *et al.*, 2016).
The fourth group is assigned to the required models to include operation into the planning stage, which is described in Section 3.4. As we discussed in Chapter 2, active management and control schemes of DERs offer non-network solutions (modify the operating conditions without changing the original network structure or deployment) that should be integrated

during the planning stage to achieve benefits from this operation capacity (Ghadi *et al.*, 2019; Li *et al.*, 2017; Xiang *et al.*, 2016).
The last group considers mathematical models for the economic framework, Section 3.5. The planning methodology must provide techno-economic analysis to evaluate the economic benefit from the decision making in the planning. Therefore, economic models have to be adopted and adapted based on the local electric markets and economic analysis strategies such as the time value of money to capture different types of cost.
Finally, the planning strategy is formed by the planning type, time-scale/planning horizon, number of planning stages (single-stage planning, stage-by-stage planning and multi-stage planning) [1] are defined for the POMMP and POMMP2 methodologies in Section 3.6.
An overview of the planning problem-solving stages is summarized in Figure **3-1**.

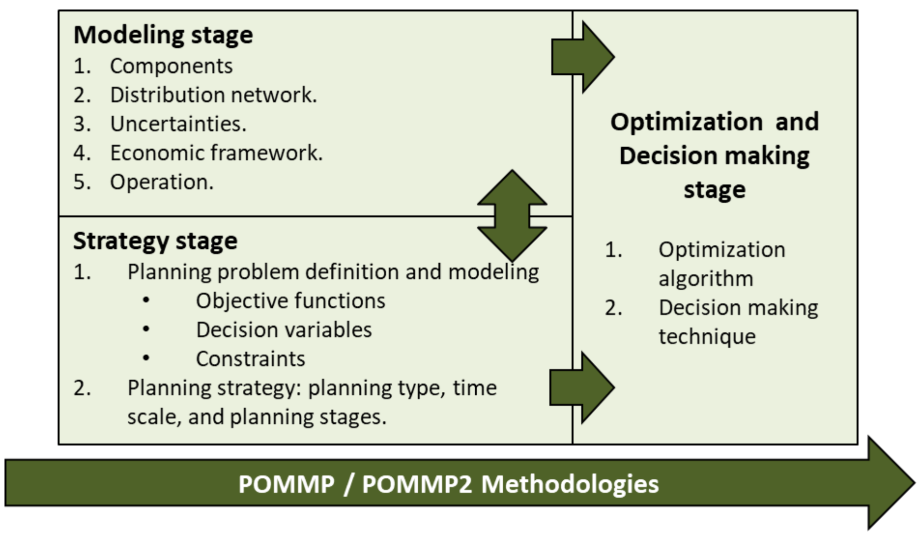

Figure 3-1.: Overview of the planning problem solving stages

The models that are described here are based on the published research by Contreras *et al.* (2018), Cortes, Contreras and Shahidehpour (2018), Contreras *et al.* (2019) Peñaranda *et al.* (2019) and Contreras *et al.* (2020b).

3.1. Mathematical models of the microgrid components

As we examined in the overview of a microgrid configuration in Chapter 2, different types of DERs technologies can be suitable for the design and operation of a microgrid. However,

[1] In stage-by-stage planning, a single stage is planned at a time and then followed by next stage; total investment and operation cost remain as in single-stage planning. In multi-stage planning, all the stage planning are carried out at the same time and the total investment and operation cost is optimized (Ehsan and Yang, 2019).

microgrids should be planned to support intentional or unintentional islanded operation either with full demand supplying or critical loads supplying. This characteristic differentiates microgrids from other "power cells"[2], since power cells will require control and permanent accessibility to energy transfer between the cell and main transmission grid, other cells or multimodal power-to-ahead or heat-to-power interfaces to guarantee the power balance of the demand inside the cell.

Therefore, to guarantee a stable and reliable operation of microgrids in both operation modes, these must include a certain capacity of directed-coupled dispatchable generation technologies or Non-conventional DERs electronically-coupled with grid-forming control capabilities (Jayaweera, 2016). In islanded mode, the DERs will be controlled to stabilize voltage and frequency while the demanded power is balanced. Thus, DER in grid forming mode emulates a swing source in a conventional grid. This is especially necessary since synchronous generators in traditional power systems have rotational inertia that supports accommodation of load changes without affecting critically the frequency stability. However, integration of DERs with smaller sizes and/or without inertia (e.g. photovoltaic systems) will lead to less inertia available, which would represent an issue for continuous islanded operation. Therefore, not only dispatchable rotating machine-based DGs but also ESS are required to ensure a stable operation of the microgrid in islanded mode. The decision making over the prospect generation matrix is a case-dependent task that can depend on different factors. A good summary of the applications and grid supporting capabilities of the DER technologies is offered by CIGRE WG C6.22 (2015a) and adapted in Table **3-1**.

Three main characteristics have been chosen as part of the planning of microgrids with POMMP and POMMP2.

1. Capability for grid-connected and islanded operation.
2. Capability for participation in current AS markets.
    - Frequency up- and down-regulation.
    - Spinning reserve.
    - Non-spinning reserve.
3. Capability for exporting electricity to the main grid.

Therefore, characteristics such as based load power supply, frequency control and islanded operation are prioritized. Consequently, from the overview of the technologies' capabilities in Table **3-1**, a base generation matrix for the planning will be composed in POMMP and POMMP2 for a set of dispatchables, non-dispatchables and storage technologies as:

[2] Power cells are defined as a locally controllable subsection of the power system with defined boundaries at the MV where DERs are interconnected via medium and low voltage AC-DC networks and power-electronics-based multimodal interfaces. Therefore, a power cell is capable to generate, distribute and consume electricity locally, and simultaneously exchange power and services with the main transmission grid, neighboring cells or multimodal power-to-gas (P2G) or power-to-heat (P2H) interfaces (Mayorga Gonzalez *et al.*, 2020).

Table 3-1.: Grid supporting and services capabilities, adapted from Kwasinski *et al.* (2016); CIGRE WG C6.22 (2015a); Barbir (2013)

<table>
<tr><th rowspan="2">DER Tech. / Services</th><th rowspan="2">Grid Coup. Tech.</th><th rowspan="2">WT</th><th rowspan="2">PV</th><th rowspan="2">Hydro</th><th colspan="2">CHP</th><th rowspan="2">MT</th><th rowspan="2">FC</th><th rowspan="2">ESS</th><th rowspan="2">Loads</th></tr>
<tr><th>T-D</th><th>E-D</th></tr>
<tr><td>Primary power supply</td><td></td><td>+</td><td>+</td><td>+</td><td>x</td><td>++</td><td>++</td><td>++</td><td>-</td><td>x</td></tr>
<tr><td>Frequency control</td><td></td><td>+</td><td>+</td><td>+</td><td>x</td><td>++</td><td>++</td><td>+</td><td>++</td><td>+</td></tr>
<tr><td rowspan="4">Voltage Control, Congestion Management, Optimization of grid losses</td><td>Inv</td><td>++</td><td rowspan="4">++</td><td>++</td><td>+</td><td>++</td><td>++</td><td rowspan="4">++</td><td>++</td><td rowspan="4">+</td></tr>
<tr><td>SG</td><td>++</td><td>++</td><td>+</td><td>++</td><td>++</td><td>++</td></tr>
<tr><td>DFIG</td><td>-</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>IG</td><td>+</td><td>-</td><td>x</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td rowspan="4">Improvement of voltage quality</td><td>Inv</td><td>++</td><td rowspan="4">++</td><td>++</td><td>++</td><td>++</td><td>++</td><td rowspan="4">++</td><td>++</td><td rowspan="4">-</td></tr>
<tr><td>SG</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td></tr>
<tr><td>DFIG</td><td>+</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>IG</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td></tr>
<tr><td rowspan="4">Black start</td><td>Inv</td><td>+</td><td rowspan="4">+</td><td>+</td><td rowspan="4">x</td><td>++</td><td>++</td><td rowspan="4">++</td><td>++</td><td rowspan="4">x</td></tr>
<tr><td>SG</td><td>+</td><td>+</td><td>+</td><td>+</td><td>+</td></tr>
<tr><td>DFIG</td><td>-</td><td></td><td></td><td></td><td></td></tr>
<tr><td>IG</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td></tr>
<tr><td rowspan="4">Islanded operation</td><td>Inv</td><td>+</td><td rowspan="4">+</td><td>+</td><td rowspan="4">x</td><td>++</td><td>++</td><td rowspan="4">++</td><td>++</td><td rowspan="4">x</td></tr>
<tr><td>SG</td><td>+</td><td>+</td><td>++</td><td>++</td><td>++</td></tr>
<tr><td>DFIG</td><td>-</td><td></td><td></td><td></td><td></td></tr>
<tr><td>IG</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td></tr>
<tr><td rowspan="4">Fault-Ride-Through</td><td>Inv</td><td>++</td><td rowspan="4">++</td><td>++</td><td>++</td><td>++</td><td>++</td><td rowspan="4">++</td><td>++</td><td rowspan="4">-</td></tr>
<tr><td>SG</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>DFIG</td><td>+</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>IG</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
</table>

DER Technologies

WT	Wind turbine	**Hydro**	Run-of-river hydro turbine	**CHP**	Combined heat and power
PV	Photovoltaic	**MT**	Microturbine	**T-D**	Thermal-driven
ESS	Energy storage system	**FC**	Fuel Cell	**E-D**	Electrical-Driven

Grid support and services capabilities

++	Indicates very good capabilities
+	Indicates good capabilities
-	Indicates little capabilities
--	Indicates very little capabilities
x	Indicates it is not possible without additional external equipment

Grid coupling technology

Inv	Inverter (included inverter coupled IG and SG)
SG	Directly-coupled synchronous generator
DFIG	Doubly-fed induction generator
IG	Directly-coupled asynchronous (induction) generator

- Dispatchable technologies
  - Rotating machine-based DG
    - Internal combustion reciprocating engines (ICE)
    - Microturbine technologies (MT)
    - Electric-driven operation of combined heat and power (CHP)
- Non-dispatchable technologies
  - Wind turbines (WT)
  - Photovoltaic units (PV)
- Storage technologies
  - Batteries (BA)

Fuel cells are dispatchable generation technologies that convert chemical energy directly into electrical energy, as batteries, with the difference that it requires a fuel flow to produce electricity Kwasinski *et al.* (2016, Chapter 5). Power cells can currently be found with capacities for primary and backup power between 1kW -10kW and some with 200kw, although Barbir (2013) claims that fuel cells would not be competitive against other technologies for applications over 250kW. Furthermore, fuel cell systems can provide electrical efficiencies up to 60% which is approximately twice that of an internal combustion engine (CIGRE WG C6.22, 2015a). Specifically, power cells are being projected as powerful alternatives to complement the future renewable-based generation matrix. However, the technology is still in a relatively early developing stage with a lack of proven track record history of commercial usage (Kwasinski *et al.*, 2016; CIGRE WG C6.22, 2015a). Hence, these alternative technologies were left out of the scope in this research, considering that this can be relatively easily included in the POMMP and POMMP2 methodologies in future research to mainly explore their impact in the selection of the overall generation matrix for particular case studies. In general, the technology by itself would not affect the methods and procedures in the planning methodology.

The mathematical models of the components were selected, adapted, and incorporated from existing models in theory to accomplish the purposes of the doctoral thesis and POMMP/POMMP2 methodologies.

3.1.1. Dispatchable DG generation

Dispatchable technologies in this dissertation have been based on either conventional or non-conventional rotating machine-based DGs, which can comprise different types of power plants (primary movers): diesel engines, gas turbine, gas engine, biomass engine, combined cycle, steam turbine, etc. Thus, dispatchable DG generation units can be reciprocating engines

(Internal combustion engines (ICE), sterling engines or steam engines) or microturbines, and can be even combined with CHP technologies. Nonetheless, microturbines have become potential dispatchable DG technologies for microgrid applications (Kwasinski *et al.*, 2016, Chapter 5; CIGRE WG C6.22, 2015a, Chapter 3; Chowdhury *et al.*, 2009, Chapter 2), reason why Figure **3-2** shows an example of a single-shaft microturbine with a CHP application.

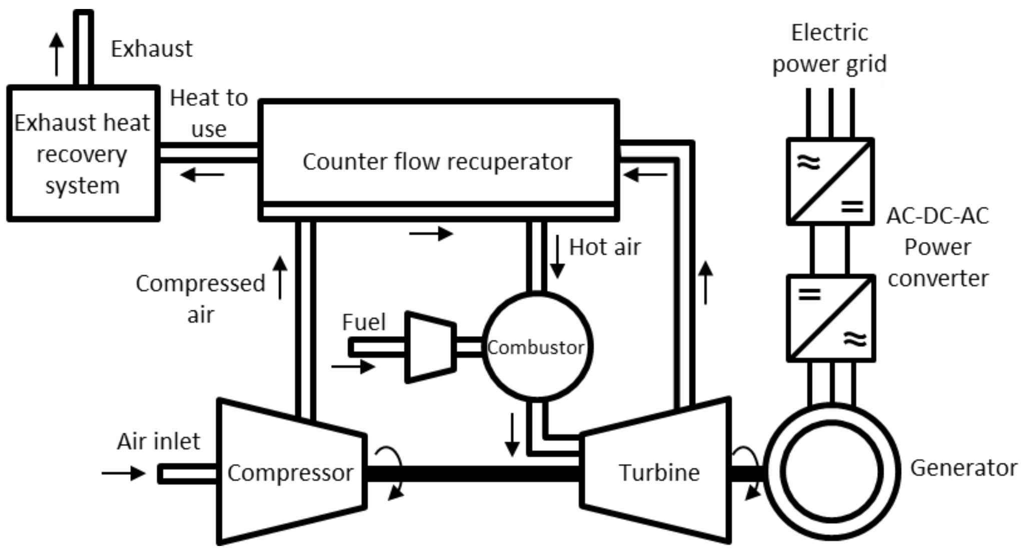

Figure 3-2.: States diagram of a single-shaft microturbine, adapted from Chowdhury *et al.* (2009)

In this context, dispatchable units are modeled as conventional generation units that can supply constant power with controlled voltage under certain power factor. Hence, dispatchable generators are defined in the buses as power-voltage-controlled units, where the output active power and voltage in the generator's buses are kept constant while the generator's output complex power fulfills the power-flow equations (3-1) and (3-2).

$$\mathrm{P}_i = \sum_{i=1}^{\mathrm{N_{bus}}} \mathrm{V}_i \mathrm{V}_j \mathrm{Y}_{ij} \cos\left(\theta_{ij} + \delta_j - \delta_i\right) \tag{3-1}$$

$$\mathrm{Q}_i = -\sum_{i=1}^{\mathrm{N_{bus}}} \mathrm{V}_i \mathrm{V}_j \mathrm{Y}_{ij} \sin\left(\theta_{ij} + \delta_j - \delta_i\right) \tag{3-2}$$

Where V_i is the magnitude of generator's output voltage (bus i voltage) with angle δ_i, and P_i and Q_i are the net active and reactive power in the dispatchable generator's bus i. In this case, the genertor's active power and voltage are defined, while the voltage's angle and generator's reactive power are determined by the mismatch power in the generator's bus, voltage V_j with angle δ_j in other buses of the microgrid and microgrid's bus admittance matrix with elements of magnitude Y_{ij} and angle θ_{ij}.

For the active and reactive power control in the rotating machine-based generators, dispatchable generators in the microgrid are assumed as steady-state synchronous machine fed from a rotating turbine. The general model of the rotating machine-based DG is shown in Figure **3-3**.

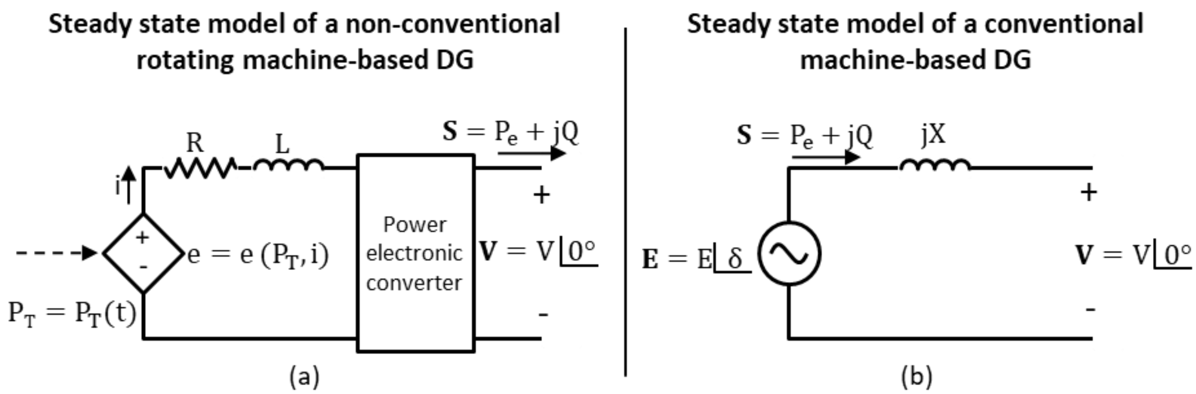

Figure 3-3.: Steady state model of a dispatchable DG, adapted from Kwasinski *et al.* (2016, Chapter 5)

As a result, the output power and voltage of both directly coupled and power-electronic coupled synchronous machines are equivalent for the planning stage. Notice that at the generation side in the electronically-coupled synchronous machine, to represent the output voltage dependency on the magnetic field intensity, the internal voltage "e" is in function of "I" (current in the rotor's dc circuit) and the turbine's power P_T (Kwasinski *et al.*, 2016). Therefore, the operation through a power electronic converter of the DG will be affected by the generator's dynamics and the turbine dynamics. However, the output from the AC-DC-AC stage addresses frequency variability caused by changes in the load and generation, which ultimately will electronically emulate the active power and rated voltage output of a synchronous machine with the advantage of being decoupled from the grid frequency effects for operation control purposes.

As it is inferred for the POMMP and POMMP2 methodologies that dispatchable generation must guarantee, whether through suitable generation machines or the use of power-electronic converters (See Figure**3-3**), complete controllability to ensure load following and power balancing as primary and secondary control frequency response during operation. Therefore, it is assumed that microgrids operate at every time step based on a unit commitment process (Contreras *et al.*, 2019; Husein and Chung, 2018). For that purpose, the approach used by Gazijahani and Salehi (2018a) is adopted, where it is assumed that renewable resources (non-dispatchable generation) operate at their maximum power generation point because of their free-fuel power generation costs and CO_2-neutral operation, and the remaining load demand is supplied by dispatchable resources as part of the unit commitment in microgrids. This approach is explained with more detail in Section 3.4.

3.1.2. Non-dispatchable DG generation

This part of the models refers to the stochastic DG units such as PV and WT. In this case, both renewable generation technologies have a common feature: **Their primary energy forms can not be deliberately controlled by the human-engineered conversion systems**. Additionally, they are considered forms of renewable and sustainable generation since not only their primary energy is replenished by nature, but also the energy conversion systems use the available energy with almost no negative influence on health and nature (Quaschning, 2014). In general, there is currently a large amount of theory and well documented basic and applied research regarding the operation principles, characteristics, design requirements, performance, etc. Therefore, in this dissertation, only a general overview of the main features of these two technologies will be addressed to explain the main features in the selected mathematical models.

The stochastic nature in the operation of the PV and WT technologies are the main source of uncertainty in the operation and consequently planning of these type of DG. Different strategies and forecasting models are currently used for the deployment of PV- and WT-based electric projects. In this research, it has been defined from the literature that the incorporation of PV and WT technologies into the POMMP and POMMP2 methodologies will require two major components: 1. Model for the mathematical energy conversion function and 2. Value of the primary energy based on uncertainty, Figure 3-4.

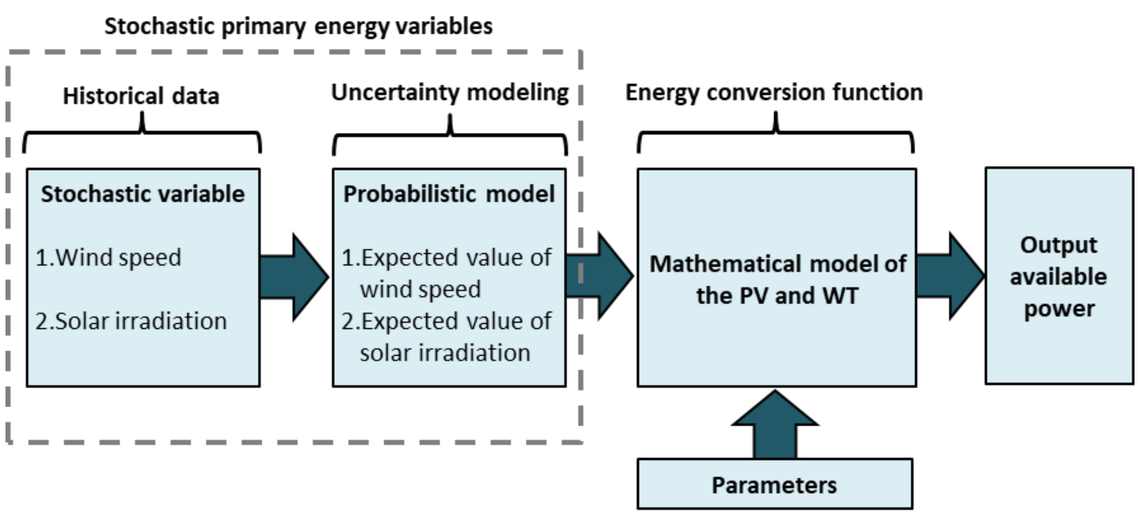

Figure 3-4.: Relation between available output power and uncertainty in the primary energy

For the planning methodologies, it is assumed that in the course of a microgrid project, maximum reachable efficiencies (maximum projected efficiencies) of technologies and installation conditions are identified and reported as inputs to the models and algorithms in the planning stage. Therefore, for planning it is granted that final selection of manufacturers, optimal setup and installation practices are part of the basic/detailed design and installation stages to achieve maximum efficiencies. For example, PV installation procedures would consider the most efficient angle inclination and orientation for the conditions of the location.

Wind turbine generators

Wind energy is related to the use of the airflow through wind turbines (WT) to transfer the kinetic mechanical energy to electric generators and convert it into electrical energy. Thus, the power contained in the wind can be calculated from the kinetic energy in equation (3-3).

$$\mathrm{P}_0 = \frac{1}{2}\rho \cdot \mathrm{A} \cdot v^3 \tag{3-3}$$

Where ρ is the density of the air mass, A the area through which the air flows, and v the wind speed in m/s.
A WT slows the wind from speed v_1 to speed v_2 and uses the corresponding power difference as it is depicted in Figure **3-5**. The power absorbed by a WT P_T can be calculated from the difference in wind speeds in equation (3-4) (Quaschning, 2014).

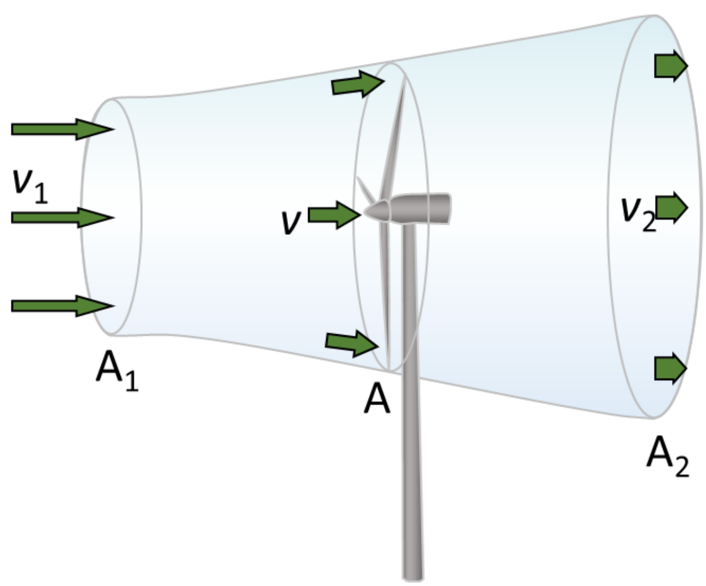

Figure 3-5.: Idealized Change of wind speed at a wind turbine

$$\mathrm{P}_\mathrm{T} = \frac{1}{2}\dot{\mathrm{m}}(v_1^2 - v_2^2) \tag{3-4}$$

Where $\dot{\mathrm{m}}$ is mass flow dm/dt for constant pressure and density ρ of the air is:

$$\dot{\mathrm{m}} = \rho\dot{V} = \rho \cdot \mathrm{A}_1 \cdot v_1 = \rho \cdot \mathrm{A}_2 \cdot v_2 = \rho \cdot \mathrm{A} \cdot \frac{1}{2}(v_1 + v_2). \tag{3-5}$$

As the mass flow dm/dt of the air does not change, the P_T becomes as in equation (3-6).

$$P_T = \frac{1}{4} \cdot \rho \cdot A \cdot (v_1 + v_2) \cdot (v_1^2 - v_2^2) \tag{3-6}$$

The ratio of the power used by the turbine P_T to the power content P_0 of the wind is called the power coefficient c_P and is given by equation (3-7) (Quaschning, 2014).

$$c_P = \frac{P_T}{P_0} = \frac{(v_1 + v_2) \cdot (v_1^2 - v_2^2)}{2 \cdot v_1^3} = \frac{1}{2}\left(1 + \frac{v_2}{v_1}\right)\left(1 - \frac{v_2^2}{v_1^2}\right) \tag{3-7}$$

The German physicist Albert Betz calculates the maximum power that can be extracted from wind independently of the WT's design. This Betz's law indicates that no turbine can capture more than $c_{p,Betz} = 16/27 = 59.3\%$ of the kinetic energy in wind. This factor is known as the Betz's coefficient and means that a turbine can extract the theoretical maximum possible power if the initial wind speed v_1 is slowed down to 1/3 ($v_2 = 1/3 \cdot v_1$). However, actual utility-scale WTs achieve at the peak a power coefficient of c_p between 40-50% (Quaschning, 2014), a value that is taken into account for the available power calculation during the planning stage. Therefore, the ratio of the used power P_T of the turbine to the maximum ideal usable power P_{id} defines the efficiency η for the power utilization of the wind in equation (3-8).

$$\eta = \frac{P_T}{P_{id}} = \frac{P_T}{P_0 \cdot c_{p,Betz}} = \frac{P_T}{\frac{1}{2}\rho \cdot A \cdot v^3 \cdot c_{p,Betz}} = \frac{c_p}{c_{p,Betz}} \tag{3-8}$$

Nonetheless, an important factor used commonly in practice is the **Tip Speed Ratio (TSR)**, which refers to the rotor power efficiency as the ratio between the actual wind speed and the speed of the tips of the WT blades, equation (3-9) (Kwasinski *et al.*, 2016).

$$(\mathrm{TSR}) = \frac{\text{rotor tip speed}}{\text{wind speed}} = \frac{N \cdot \pi \cdot D}{60 \cdot v} \tag{3-9}$$

Where N is the revolutions per minute of the rotor blades, v is the wind speed at the rotor and D is the diameter of the circle described by the tips of the blades when they rotate. The TSP characteristic varies with the design of the rotors and for each wind speed, there is an optimal rotor speed that reaches the maximum efficiency for the rotor. This means that for a given wind speed, the rotor speed is adjusted to the one that achieves the maximum efficiency to optimize the rotor efficiency (Kwasinski *et al.*, 2016). Therefore, WTs use rotor speed control systems to achieve maximum efficiency at a given wind speed. Some control strategies include the TSR control method, power signal feedback control and the hill-climbing searching control.

Currently, a commonly used control approach to maximize the performance of the turbine is based on controlling the power output instead of the rotor speed. For that reason, a DC-DC converter (usually a boost converter) is included between the output of the rectifier to guarantee that the WT operating point lies on the optimal power line P_{mopt}, indicated indicated in Figure **3-6** (Kwasinski *et al.*, 2016).

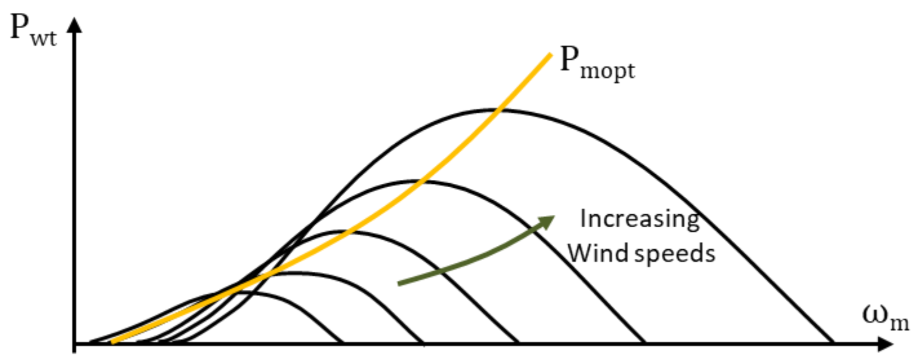

Figure 3-6.: Wind turbine output power versus rotor angular speed characteristics, adapted from Kwasinski *et al.* (2016)

Additionally, WTs operate at sub-optimal regimes during high wind conditions in order to avoid exceeding the rated power of the coupled electric generator and maintain its operation at this maximum value. During this operation regime, the rectified output current is limited in order to maintain its output power under its maximum rated value (Kwasinski *et al.*, 2016). A next point in the control operation is achieved with extra high wind speed when mechanical limits are reached and braking systems are activated. This is the cut-out point. Therefore, a final typical WT generator operation characteristic will look as in Figure **3-7**

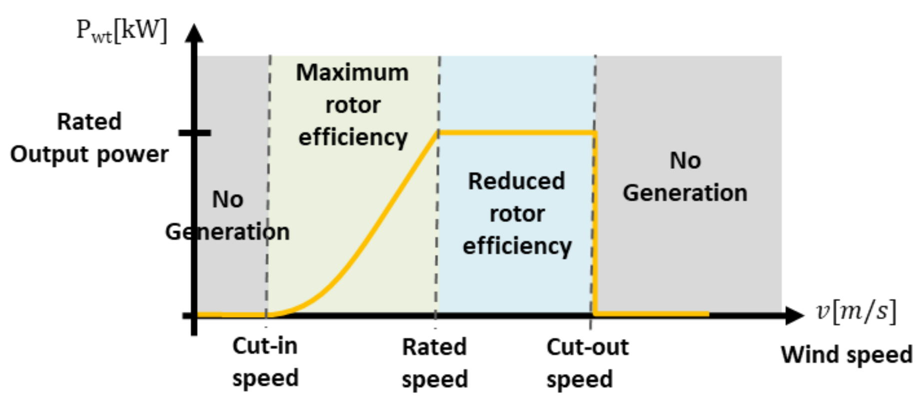

Figure 3-7.: Wind turbine generator operation characteristic, adapted from Kwasinski *et al.* (2016)

It is expected that in future optimally controlled WTs are implemented in microgrids. Therefore, this operation characteristic was adopted for the calculation of the output power of the WTs generators in the planning methodologies as other authors, for example Arevalo *et al.* (2017) and Arefifar and Mohamed (2014b), have implemented for both microgrid operation scheduling and planning. The mathematical expression for the energy conversion function in the operation is shown in equation (3-10).

$$\mathrm{P_{wt}}(v) = \begin{cases} 0, & \text{for} \quad v < v_\mathrm{i} \text{ and } v > v_\mathrm{o} \\ \mathrm{Pr_{wt}} \frac{(v - v_\mathrm{i})}{v_\mathrm{r} - v_\mathrm{i}}, & \text{for} \quad v_\mathrm{i} \leq v < v_\mathrm{r} \\ \mathrm{Pr_{wt}}, & \text{for} \quad v_\mathrm{r} \leq v \leq v_\mathrm{o} \end{cases} \tag{3-10}$$

Where $\mathrm{P_{wt}}$ is the available output active power; $\mathrm{Pr_{wt}}$ is the rated power of the WT; and v_i, v_r and v_o are the cut-in, rated and cut-out wind speed, respectively (Contreras *et al.*, 2019). As a reference, in meteorology, the Beaufort scale is often applied to define the wind force (Bf-Beaufort force), Table **3-2**.

Table 3-2.: Wind speed classification of the Beaufort wind scale

Bf	v **in m/s**	**Description**	**Effects**
0	0-0,2	Calm	Smoke rises vertically
1	0,3-1,5	Light air	Smoke moves slightly and shows direction of wind
2	1,6-3,3	Light breeze	Wind can be felt. Leaves start to rustle
3	3,4-5,4	Gentle breeze	Small branches start to sway. Wind extends light flags
4	5,5-7,9	Moderate breeze	Larger branches sway. Loose dust on ground moves
5	8,0-10,7	Fresh breeze	Small trees sway
6	10,8-13,8	Strong breeze	Trees begin to bend, whistling in wires
7	13,9-17,1	Moderate gale	Large trees sway
8	17,2-20,7	Fresh gale	Twigs break from trees
9	20,8-24,4	Strong gale	Branches break from trees, minor damage to buildings
10	24,5-28,4	Full gale/storm	Trees are uprooted
11	28,5-32,6	Violent storm	Widespread damage
12	$\geq$ 32,7	Hurricane	Structural damage

WTs can operate with different types of generators such as induction machines, doubly-fed generators, and synchronous machines. Despite some applications also admit direct coupling to the network, it has been assumed for the POMMP and POMMP2 methodologies that all WTs are power electronically coupled to the main grid with synchronous generation technologies or are equipped with doubly-fed induction generators (or wound-rotor doubly-fed generators) with proper AC-DC-AC frequency and phase control of the excitation currents and generator output power to follow the operation characteristic in Figure **3-7**. These two main connections of the WTs to the main grid were shown in Figure **2-5** in Chapter 2.

Photovoltaic systems

A photovoltaic system uses solar panels (modules) that contain a certain number of solar cells manufactured with semiconductor materials for generating electrical power. One advantage of the PV systems is their high versatility due to their modularity, while one disadvantage of the PV is its stochastic operation and dependency of several factors that affect its efficiency. A deep explanation of the technologies can be amply studied in the literature such as (Quaschning, 2014; Patel, 2005).
In this dissertation, the most relevant PV characteristics will be summarized to calculate the available power of a PV system for the POMMP and POMMP2 methodologies. The operational aspects that influence the design and operation of a PV system are (Quaschning, 2014):

- Available solar irradiation (time series) and sunshine duration.
- Panels location, modules size and sunlight angle
- Environmental and surrounding conditions: temperature, dust (dirt), shadows and reflections
- Load power demand and voltage specifications. Load matching for maximum power
- Size and efficiency of charger, inverter, cables, adaptors, etc.

The non-irradiated solar cell ($E = 0$) performs approximately like a diode, so a simple equivalent circuit of a diode can describe the solar panel behavior. The simple equivalent circuit is sufficient for most applications, although sometimes a more accurate model is necessary for dynamic and transitory studies. In these cases, an extended equivalent circuit with one or two diodes and a resistor in series to simulate the voltages drops in the semiconductor junctions and a parallel resistor to consider the leakage currents can be considered (Quaschning, 2014). However, for steady-state studies, for example in the planning methodologies, the simple model can be used for the main calculations. The analysis of the PV cells based on the diode physical behavior will show that the PV under irradiation E will produce a circuit voltage difference for a current proportional to the irradiation which also depends on the temperature of the material. Thus, the current-voltage characteristic depending on the irradiation and the temperature[3] are shown in Figure 3-8.
From Figure 3-8 it can be deduced that the solar cell generates maximum power at a certain voltage. This point is called **Maximum Power Point - MPP** as it is shown in Figure 3-9. The MPP is given by equation (3-11).

$$\mathrm{P_{MPP}} = \mathrm{V_{MPP}} \cdot \mathrm{I_{MPP}} < \mathrm{V_{oc}} \cdot \mathrm{I_{sc}} \tag{3-11}$$

[3]Basically, the increase of temperature will cause an increase of the saturation currents and consequently decrease in the open-circuit voltage.

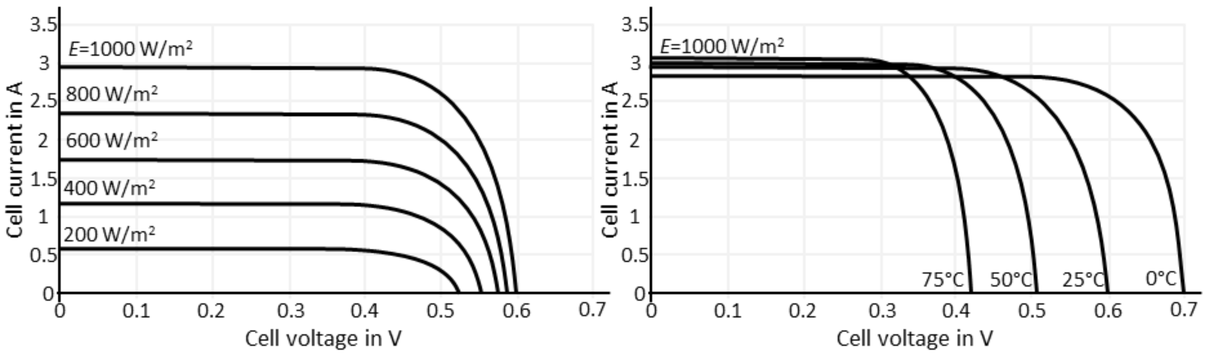

Figure 3-8.: Typical I-V characteristics of PV cells at various cell temperatures and irradiance levels - maximum power of 1.8W, adapted from Quaschning (2014)

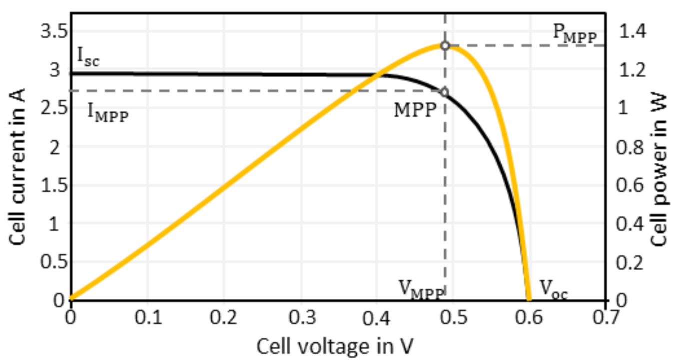

Figure 3-9.: I-V and P-V solar cell characteristics with Maximum power point (MPP), adapted from Quaschning (2014)

Where V_{MPP} is the MPP voltage and I_{MPP} is the current at the MPP, while V_{oc} is the open-circuit voltage and I_{sc} the short circuit current. The P_{MPP} is normally measured under standard test conditions (STC) since the operation is affected by the temperature and other external conditions. The STC are indicated below.

- Solar irradiation $E = 1000\text{W/m}^2$
- Modules temperature $\vartheta = 25°\text{C}$
- Solar spectrum (it describes the atmosphere losses) $\text{AM} = 1,5$

PV systems can be designed for stand-alone, hybrid-stand-alone, or grid-connected applications. For the POMMP and POMMP2 methodologies, a grid-connected design will be considered, which means that the PV systems will be at all times interconnected with the microgrid. The available PV system (set of interconnected PV modules) output power P_{pv} in terms of the global solar irradiation E_g can be calculated in equation (3-12) under STC (Quaschning, 2014).

$$P_{pv} = Pr_{pv} \cdot \frac{E_g}{E_{stc}} \cdot f_{inclined} \cdot \eta_{sys} \quad [W] \tag{3-12}$$

Where the rated power Pr_{pv} that correspond to the P_{MPP} for the STC is given in equation (3-13).

$$Pr_{pv} = [A_{Module} \cdot \eta_{rated} \cdot E_{stc}] \quad [W_p] \tag{3-13}$$

Pr_{pv} is the PV system rated (installed) power, A_{Module} is the single PV module's area, η_{rated} is the rated module's efficiency and E_{stc} is the solar irradiation for the STC. The units for the rated power is normally given in W_p in Watt-peak, and the rated power for a PV system (Parallel or series interconnection of modules) would be Pr_{pv} times the number of PV modules in the PV system N_{PV}. In equation (3-12), E_g is the global solar irradiation, $f_{inclined}$ is the gains and losses due to modules inclination and orientation, and η_{sys} is the PV system efficiency that considers additional loss parameters that affect the rated efficiency of the PV modules.

- Losses in the inverters, $(1 - \eta_{inverters})$ approx. 3-9% of losses.
- Losses due to reflections, $(1 - \eta_{reflection})$ approx 3-5% of losses.
- Losses of the connections, $(1 - \eta_{connection})$.
- Temperature effect, $\eta_{temperature}$.
- Shadows and irregularities effect $\eta_{shading}$.

Therefore, in practice, the design of the PV system must consider different source losses, which would lead to a η_{sys} as in equation (3-14).

$$\eta_{sys} = \eta_{rated} \cdot (1 - \eta_{inverters}) \cdot (1 - \eta_{reflection}) \cdot (1 - \eta_{connection}) \cdot \eta_{temperature} \cdot \eta_{shading} \tag{3-14}$$

However, sometimes η_{sys} is replaced for a standard performance ratio PR, whose typical values are given in Table **3-3** (Quaschning, 2014).
To sum up, the magnitude of the photocurrent is maximum for full solar radiation and decreases directly proportionally to the sun intensity. However, the cell's rated efficiency is practically insensitive to the solar radiation in the practical operation range as it is shown in Figure **3-10** (Patel, 2005; Marwali Haili *et al.*, 1998).
As Marwali Haili *et al.* (1998) explain, at the beginning a small increase in the irradiation gives rise to a significant increase in the PV efficiency. However, after a certain radiation

Table 3-3.: Typical performance ratio for PV systems

State of application	PR
Very good system with good rear ventilation, no shadowing, low module pollution	0,85
Average system	0,75
Average system with small losses concerning shadowing and bad rear ventilation	0,7
Bad system with losses concerning shadowing and pollution, malfunctioning of the system	0,6

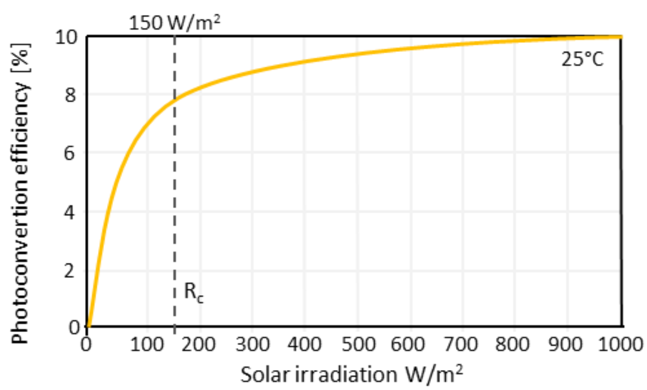

Figure 3-10.: PV efficiency versus solar irradiation, adapted from Patel (2005); Marwali Haili *et al.* (1998)

point, normally denoted with $\mathrm{R_c}$ (Park *et al.*, 2009; Liang and Liao, 2007), further increases in irradiation lead to a relatively small change in the PV efficiency. Therefore, as Patel (2005) claims, the PV conversion efficiency is equal on a bright sunny day and a cloudy day, and only solar irradiance is responsible for lower or higher power output together with external factors such as sun angle, operating temperature, shading, etc.
Based on this feature of the PV cells, Marwali Haili *et al.* (1998) define the output power of the PV as function of the solar irradiance, $P_{pv}(E_{\mathrm{g}})$, in $[W/m^2]$ as in equation (3-15).

$$\mathrm{P_{pv}}(E_{\mathrm{g}}) = \begin{cases} \frac{\eta_{\mathrm{rated}}}{\mathrm{R_c}} \left(E_{\mathrm{g}}\right)^2, & \text{for} \quad 0 \leq E_{\mathrm{g}} < \mathrm{R_c} \\ \eta_{rated} \cdot E_{\mathrm{g}}, & \text{for} \quad E_{\mathrm{g}} > \mathrm{R_c} \end{cases} \tag{3-15}$$

Considering that η_{rated} is given for the STC as in equation (3-16) (Patel, 2005).

$$\eta_{\mathrm{rated}} = \frac{\text{Electrical power output}}{\text{Solar power impacting the cell}} = \frac{\mathrm{Pr_{pv}}}{E_{\mathrm{str}}} \tag{3-16}$$

Equation (3-15) was rewritten by Liang and Liao (2007) and expanded by Park *et al.* (2009) in the so-called "solar radiation-to-energy conversion function" for the available output power for a given irradiance in equation (3-17).

$$\mathrm{P_{pv}}\left(E_{\mathrm{g}}\right)=\begin{cases}\mathrm{Pr_{pv}}\left(\frac{E_{\mathrm{g}}^{2}}{E_{\mathrm{str}}\cdot \mathrm{R_c}}\right), & \text{for} \quad 0\leq E_{\mathrm{g}}<\mathrm{R_c}\\ \mathrm{Pr_{pv}}\left(\frac{E_{\mathrm{g}}}{E_{\mathrm{str}}}\right), & \text{for} \quad \mathrm{R_c}\leq E_{\mathrm{g}}\leq E_{\mathrm{str}}\\ \mathrm{Pr_{pv}}, & \text{for} \quad E_{\mathrm{g}}>E_{\mathrm{str}}\end{cases} \tag{3-17}$$

Where accordingly to (Park *et al.*, 2009; Liang and Liao, 2007).

- $\mathrm{P_{pv}}$: PV output power before considering performance ratio [kW]
- E_{g}: Solar irradiation from uncertainty model in [W/m^2]
- E_{str}: Solar radiation in the standard environment set usually as 1000 [W/m^2]
- $\mathrm{R_c}$: A certain radiation point set usually as 150 [W/m^2]. After this point rated efficiency's can be consider constant for solar irradiation, Figure **3-9**.
- $\mathrm{Pr_{pv}}$: Equivalent rated capacity of the PV [kW]

The PV power output model from the energy conversion function in equation (3-17) can be graphically represented as in Figure **3-11**.

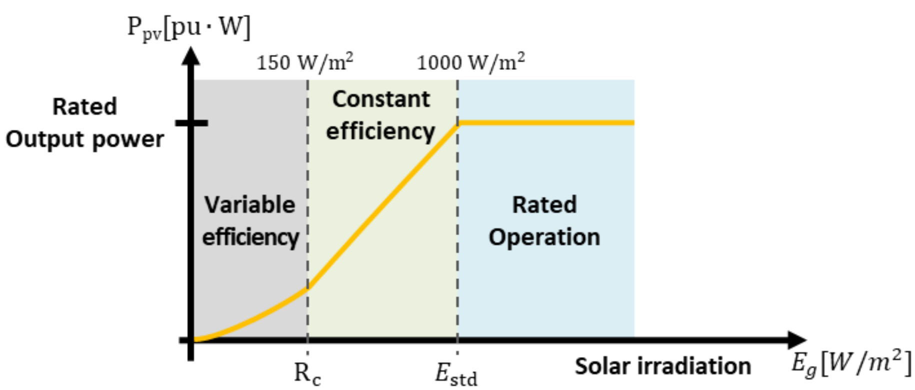

Figure 3-11.: Power output model of a PV system, adapted from Park *et al.* (2009)

The power output model presented in equation (3-17) and Figure **3-11** has been described and successfully implemented in recent studies (Arevalo *et al.*, 2017; Surender Reddy *et al.*, 2015; Kyriakides *et al.*, 2015; Park *et al.*, 2009; Liang and Liao, 2007). Therefore, the model and energy conversion functions were adopted for the mathematical models of the PV systems in the POMMP and POMMP2 methodologies. In this case, to include the effect of external factors such as temperature and shadows effects, a performance ratio for very

good systems (0.85) is used together with the power equation to calculate the effective PV output power. Furthermore, it is assumed that the PV systems are designed with a proper inclination and orientation accordingly to the geographical location and irradiance condition that gives rise to an inclination factor equal to 1.
Additionally, it is considered for the planning task that the PV power electronic interfaces are properly set up to operate the PV modules at their MPP and to control the output of the PV system. Different approaches and configurations (e.g. series or parallel modules connection) have been proposed and used to accomplish control and performance goals. Currently, two main strategies and cost-benefit decisions are based on the use of a single power electronic interface for the whole, or big section, of a PV system (array), or the use of a power electronic interface for each PV module, which are called module-integrated inverters or microinverters (Quaschning, 2014).
The selection of one or another configuration affect planning from the PV system efficiency factors and installation costs, which can be easily configured as part of the POMMP and POMMP2 methodologies depending on the case study. The decision making behind the architectures are out of the scope of the planning methodology, and preliminary studies must project and provide the possible systems information as inputs for planning.

3.1.3. Energy storage systems - Batteries

As we discussed before, batteries are being positioned as a very convenient technology for microgrids and other ADNs. For this reason, the mathematical model for the operation of battery technologies will be considered as part of the POMMP and POMMP2 methodologies, Figure **3-12**.

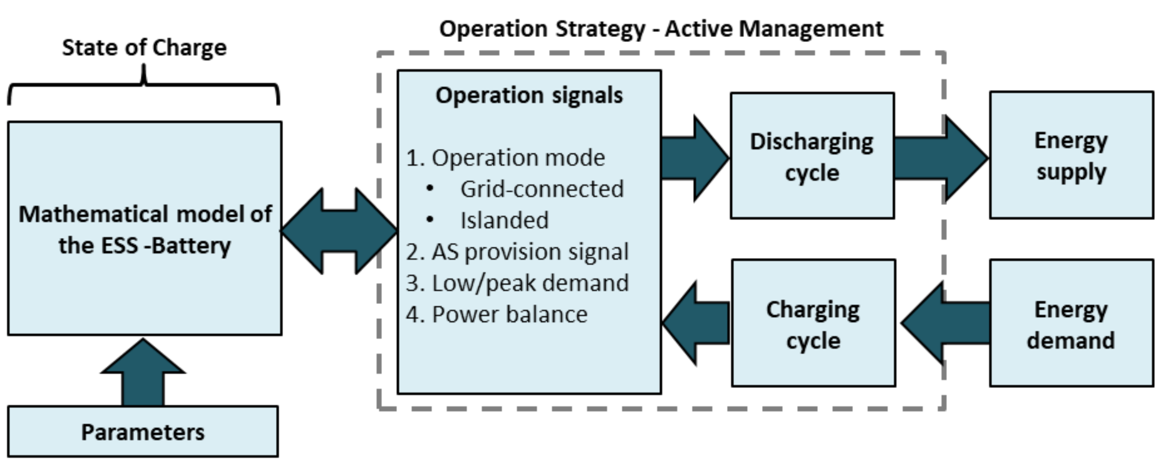

Figure 3-12.: Relation between the operation strategy and the demand or supply of energy

In this section the mathematical model for the ESS - Batteries will be studied, while the main operation strategies for active management of the storage resources for deterministic charging/discharging (C/D) cycles will be discussed in Section 3.4 of the operation models.

Main features of the batteries operation

Although there are different types of batteries with diverse constructive characteristics, in general, the operation of batteries is governed by the charging / discharging cycles (C/D), and basic performance characteristics that influence their operation (Quaschning, 2014; Patel, 2005):

- Capacity C
- C/D voltages,
- C/D ratio,
- C/D energy efficiency,
- The lifespan in terms of the number of C/D cycles.

In principle, the type of battery does not affect the planning procedures in the methodologies. However, manufacturing characteristics such as cost, rated capacity, efficiency and lifespan will be inputs for the POMMP and POMMP2 methodologies.

The ESS, batteries, in this case, have a representative role in the microgrids depending on the operation mode. The battery capacity C is measured in Amperes-hour (Ah) and the energy rating during C/D in watt-hour (Wh)[4]. However, accordingly, to CIGRE WG C6.22 (2015a), an ESS normally aims to control and maintain a specific target **State of Charge (SOC)** during operation cycles to ensure enough reserve energy capacity for response to operation signals, renewable generation smoothing, peak shaving, islanded operation or other generation and load management services. Therefore, the mathematical model for the batteries in the POMMP and POMMP2 methodologies is based on the time-dependent definition of the SOC and the discharging and charging energy.

The accuracy level of the mathematical model involves higher orders and nonlinearities to observe their dynamic operation. Thus, for the planning methodology, it is considered that batteries operate in steady-state conditions and are interconnected with the microgrid using power electronics. Therefore, a simple first-order model can offer the required accuracy in the planning stage to indicate the C/D power, Figure **3-13**.

The model represents the battery side and the grid side. It is noticeable that an AC voltage and complex power will be delivered or demanded to the microgrid through the power electric

[4]The capacity means that a battery can deliver C amperes for one hour or C/n amperes for n hours. Then, the C/D rates are normally presented in units of its capacity in Ah. e.g Discharging a C = $50Ah$ battery at 1C means the battery will be discharged in 1h with a current of 50A or C/2 means the battery will be discharged at 25A in 2h.

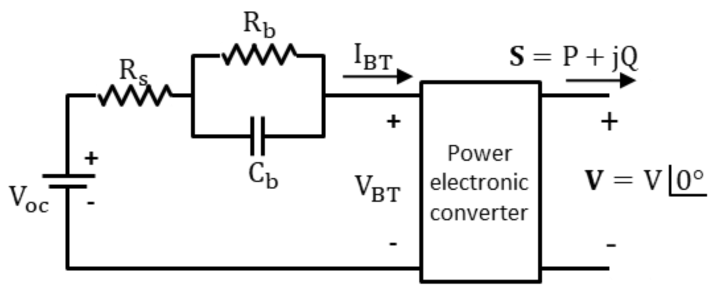

Figure 3-13.: Equivalent circuit for the batteries model, adapted from Kwasinski *et al.* (2016)

converter (normally an inverter). Consequently, it is required to calculate at the battery side the power capacity to be delivered during the discharging cycle and the power demanded to be consumed during the charging cycle for the planning process. A typical C/D cycle for a Li-ion battery using a constant-current charging profile is shown in Figure **3-14** (Kwasinski *et al.*, 2016).

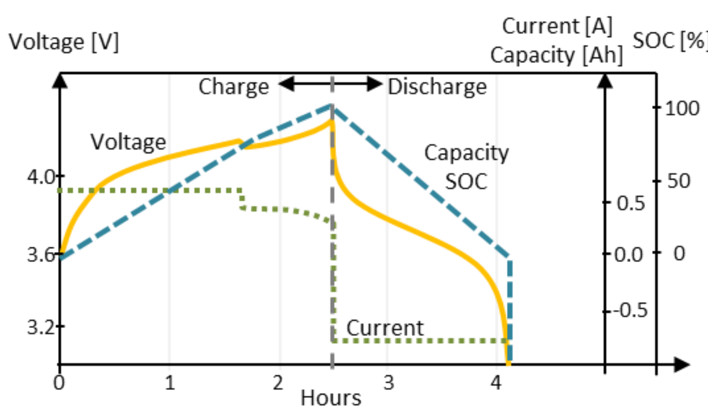

Figure 3-14.: Typical charge/discharge cycle of a battery, adapted from Kwasinski *et al.* (2016)

It should be considered that the C/D cycles are not ideal, then there is an efficiency associated with each of the cycles and between the cycles. This is explained by Kwasinski *et al.* (2016) considering that the battery is charged during a time Δt_{ch} with a constant current I_{ch} and an approximately constant voltage V_{ch}. In this way, the energy transferred by the battery E_{ch} is given by equation (3-18).

$$E_{ch} = V_{ch} \cdot I_{ch} \cdot \Delta t_{ch} \tag{3-18}$$

Now, considering that the current I_{dch} and voltage V_{dch} are constant during the discharging cycle that needs a time Δt_{dch} to achieve a SOC equal to the SOC at which the charging cycle started before, the energy delivered by the battery during the discharging cycle is given by equation (3-19).

$$E_{dch} = V_{dch} \cdot I_{dch} \cdot \Delta t_{dch} \tag{3-19}$$

The energy efficiency will be the ratio between the energy consumed during charging and the energy delivered during discharging, equation (3-20) (Kwasinski *et al.*, 2016).

$$\eta_E = \frac{E_{dch}}{E_{ch}} = \frac{V_{dch} \cdot I_{dch} \cdot \Delta t_{dch}}{V_{ch} \cdot I_{ch} \cdot \Delta t_{ch}} \tag{3-20}$$

The energy efficiency is also related with the C/D ratio that is the ratio between the Ah input ($I_{ch} \cdot \Delta t_{ch}$) and the Ah output ($I_{dch} \cdot \Delta t_{dch}$). The C/D ratio is useful since it indicates the percentage of extra required charging Ah with respect to the discharging Ah to return to an initial SOC (or full SOC). Furthermore, the C/D rate is influenced by temperature (Patel, 2005) since internal resistance R_s varies with the change of temperature.

Other efficiencies in the battery are the charge and discharge efficiency and self-discharge. These efficiency characteristics depend also on temperature. Patel (2005) describes that the charge efficiency is almost 100% when the SOC is zero. However, in real applications, when the SOC comes close to 100%, the charging efficiency falls up to zero, where the inflection point depends on the charge rate. For example, at C/2 charge rate, the charge efficiency is 100 percent up to a SOC value of about 75%. Additionally, a battery out of service has a self-discharging rate, which is regularly lower than 1% per day and it is normally controlled with a so-called trickle charge system to maintain a full SOC (Patel, 2005). Typical battery's charging efficiency, discharging efficiency and self-discharge percentage for a certain operating temperature are given by Patel (2005, Chapter 10).

Model of the state of charge for the planning problem

Many authors have used mathematical models based on defined capacities and constant periods of C/D for solving planning problems with ESS. For example, Gazijahani and Salehi (2018b, 2017) assume that the ESS operate as loads (charge) in low load periods and operate as sources in peak load hour (discharge). Conversely, in the POMMP and POMMP2, the approaches in (Hidalgo-Rodriguez and Myrzik, 2018; Guo *et al.*, 2016; Fathima and Palanisamy, 2015) were adapted. Correspondingly, the **battery system** C/D power will depend on the rated capacity in [Wh], voltage and battery charging, discharging efficiency, while the C/D condition will be commanded by the active management strategies described in Section 3.4 and a time-dependent definition of the battery's SOC in equation (3-21).

$$SOC\,(t + \Delta t) = SOC\,(t)\,(1 - \eta_{ba}) \pm \frac{E_{ba}}{C_{ba}} \tag{3-21}$$

Where $\mathrm{SOC}_{t+\Delta t}$ and SOC_t are the SOC for the time step t and $t+\Delta t$; η_{ba} is the self-discharge coefficient; E_{ba} is the input/output energy of the battery in [Wh], which is positive during the charging cycle and negative over the discharging cycle; and C_{ba} is the rated battery capacity in $[Wh]$. The battery input/output energy of the battery is given for the charging $\mathrm{E}_{\mathrm{ba}}^{\mathrm{ch}}$ and discharging $\mathrm{E}_{\mathrm{ba}}^{\mathrm{dch}}$ cycles as in equation (3-22).

$$\mathrm{E}_{\mathrm{ba}}(\mathrm{SOC}) = \begin{cases} P_{ba}^{ch} \cdot \Delta t_{ch} \cdot \eta_{ch} & \text{if } SOC \leq minSOC \\ -P_{ba}^{dch} \cdot \Delta t_{dch} \cdot 1/\eta_{dch} & \text{if } SOC = 1 \end{cases} \tag{3-22}$$

Where $\mathrm{P}_{\mathrm{ba}}^{\mathrm{ch}}$ and $\mathrm{P}_{\mathrm{ba}}^{\mathrm{dch}}$ are the charge and discharge power, Δt_{ch} and Δt_{dch} the charging and discharging time, and η_{ch} and η_{dch} are the charging and discharging efficiency, respectively. Notice that Δt_{ch} and Δt_{dch} will correspond to the time step Δt and minSOC is the minimum acceptable SOC or maximum Depth of Charge (DOC).

Notice that the POMMP and POMMP2 methodologies are defined based on the operation of the system in typical days of 24 hours and time steps of 1h along the planning horizon (See Section 3.6). Therefore, the Δt will be equal to one hour for planning simulations (Contreras *et al.*, 2020b, 2019).

The mathematical model considers inputs for battery charging, discharging and self-discharge efficiency. Although the battery's efficiency is not constant and depends on factors such as temperature, SOC and C-rate, the efficiency for the models are assumed constant for the planning purposes. This is considered since efficiency variation is relatively small for normal operation conditions (Patel, 2005) and distributed battery systems are normally installed in transportable containers or permanent operation rooms with controlled ambient temperature when it is required. For example, Patel (2005, Chapter 10) presents a table with characteristic temperatures and efficiency dependency. In this, the charging efficiency variates between 93% and 91%, discharging efficiency is constant in 100% and the self-discharge factor variates between 0.2 and 1.0 % capacity/day for temperatures between 0°C and 30°C. As a general rule, the charging efficiency is always lower than the discharging efficiency, which is implicit to the definition of the battery efficiency (Patel, 2005).

The delivered or demanded power by the battery in the time step t is given by the rated voltage of the battery system, current depending on system's capacity and C-rate based on the total C/D time windows in the operation strategies as it is shown in equations (3-23), (3-24).

$$\mathrm{P}_{\mathrm{ba}}^{\mathrm{ch}} = \mathrm{V}_{\mathrm{ba}}^{\mathrm{ch}} \cdot \mathrm{I}_{\mathrm{ba}}^{\mathrm{ch}} = \frac{\mathrm{C}_{\mathrm{ba}}}{t_{total}^{ch}} \tag{3-23}$$

$$\mathrm{P}_{\mathrm{ba}}^{\mathrm{dch}} = \mathrm{V}_{\mathrm{ba}}^{\mathrm{dch}} \cdot \mathrm{I}_{\mathrm{ba}}^{\mathrm{dch}} = \frac{\mathrm{C}_{\mathrm{ba}}}{t_{total}^{dch}} \tag{3-24}$$

Accordingly, the battery system size is planned based on the rated power (independent decision variable) that corresponds to $\mathrm{P}_{\mathrm{ba}}^{\mathrm{ch}}$ and $\mathrm{P}_{\mathrm{ba}}^{\mathrm{dch}}$. Afterward, the commercial rated capacity (dependent decision variable) is defined in Wh for pre-defined minimum/maximum C-rates based on expected C/D cycles of a pre-specified operation strategy that will be studied in Section 3.4. Furthermore, the battery system capacity in Ah is defined based on commercially selected batteries' rated voltages and conventional arrays of series and parallel series-sets interconnected batteries arrays.

Example: It is planned a battery system for 10kW load demand with active management in such as way that the battery can entirely be charged during the low demand period of 12 hours, and can supply the load during high demand period of 12 hours. Neglecting efficiency ratios in the C/D cycle in this example, the planning strategy would find a 10kW battery system optimal, while the rated battery system capacity would be selected as 120kWh for operation with C/12 rate. Considering a predefined 24V batteries in an array of 10 batteries in series and 10 sets of series in parallel (100 batteries), the battery system would operate with a rated voltage of 240V (10×24V), the batteries system would have a C = 500Ah (120kWh/240V) and the discharging current for C/12 would be 41.6A (500Ah/12h). Therefore, each battery would be sized for a capacity of C = 50Ah, 24V and would be discharged at C/12 with a current of 4.16A.

The battery system rated power for a C-rate condition are planning variables for the POMMP and POMMP2 methodologies, while the final battery array and individual specification provide the required estimation of the battery system's deployment cost.

3.1.4. Mathematical model for loads

Microgrids can comprise different types of loads depending on the microgrid, stakeholders and case study. In general, loads can be passive elements in the microgrid that involve different stochastic electric consumption rates, or can also be active elements that dynamically interact with the DERs in the microgrid. These types of loads are considered as active or flexible loads, which can be defined as controlled loads that can voluntarily change their power consumption and participate in the operation and control of the microgrid (Yang *et al.*, 2018). For that purpose, flexible loads will be interconnected with the microgrid through power electronic converter interfaces. For the POMMP and POMMP2 methodologies, the planning of specific flexible loads was left out of the scope considering that extensive use of flexible loads is still a recent research topic that will require extensive research in the future (Yang *et al.*, 2018). Therefore, loads were defined for the planning methodologies as a steady-state, balanced, PQ model, Figure **3-15**.

The load demand is considered a stochastic variable for the POMMP and POMMP2 methodologies. Therefore, uncertainty modeling for the load demand is explained in Section 3.3.

Additionally, a load shedding capability in islanded mode operation was studied in the first approximation to the POMMP methodology of Contreras *et al.* (2018) to evaluate the

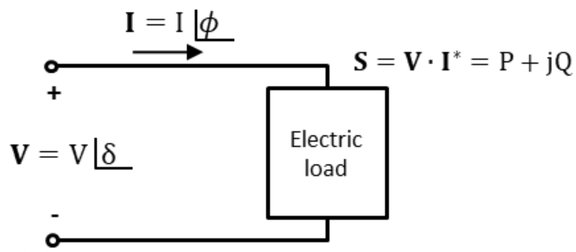

Figure 3-15.: PQ model for loads in the microgrid planning

impact of the size and location of the DERs regarding the maximization of the residual power capacity in grid-connected mode.

3.1.5. Mathematical model for power electronic converters

As we have described previously, most DERs and flexible loads will require a power electronic converter interface in the future for operating within the microgrid (Chowdhury *et al.*, 2009). Particularly, converters are an essential component not only for the use of DC sources in AC networks but also for ensuring system security and optimal operation management through central and local control systems in the microgrid[5] (Chowdhury *et al.*, 2009).

However, from the expansion and resources planning point of view, the main impact of power electronic interfaces is the final output of the active/reactive power and voltage control, added control functions (e.g. active management functions) and associated installation, operation and maintenance costs of the equipment. These characteristic offers advantages for planning simulation purposes. For example, the converter can provide voltage and frequency regulation under any operating condition to emulate the inertial capability of conventional synchronous machines to adjust the mismatch in generation and demand. Therefore, steady-state power flow simulations can be executed in the planning stage under the assumption of the conventional PV model and PQ models. This can be better visualized in the mathematical modeling of DERs with power converters in Figure **3-16**.

In all cases, the voltage source inverter in the power electronic converter system controls both magnitude and phase angle of the output voltage $\mathbf{V_1} = \mathrm{V}_1\underline{/\delta_1}$. Thus the DER provide controlled power to a second bus of the microgrid at voltage $\mathbf{V_2} = \mathrm{V}_2\underline{/\delta_2}$ through the line with impedance $\mathbf{Z} = j\mathrm{X}$. Therefore, the active power flow P is controlled by controlling δ, while reactive power Q is controlled by controlling V_1. The controls are based on feedback loops of output power P and microgrid bus voltage magnitude V_2 as in a traditional network with the equations (3-25) and (3-26) (Chen *et al.*, 2015; Sahoo *et al.*, 2018).

[5]The converters normally used in DERs application in microgrids are single-phase two-level, three-phase two-level or three-phase three-level voltage source converters.

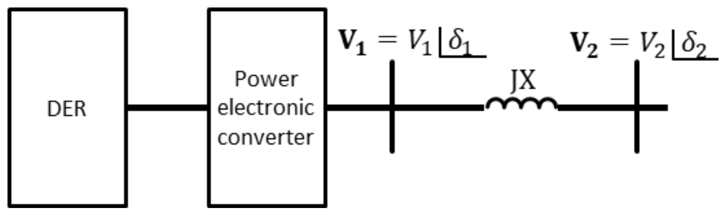

Figure 3-16.: Scheme of the DER's power electronic converter-based interconnection, adapted from Chowdhury *et al.* (2009)

$$\mathrm{P} = \frac{\mathrm{V_1 V_2} \sin(\delta)}{\mathrm{X}} \tag{3-25}$$

$$\mathrm{Q} = \frac{\mathrm{V_1 V_2} \cos(\delta) - \mathrm{V_2}^2}{\mathrm{X}} \tag{3-26}$$

Furthermore, converters will use voltage–reactive power (V-Q) droop controllers to control the large circulating reactive currents among DERs (Chowdhury *et al.*, 2009). The inverter increases the local voltage set point when reactive currents become mainly inductive and decrease the set point when the current becomes capacitive. Therefore, for planning purposes, it is set up a VA rating for the reactive power limit of the DERs with a power electronic converter interface, and the buses are defined as PQ buses. Hence, the reactive power will depend on the VA rating and active power delivered by the DERs according to equation (3-27).

$$\mathrm{Q_{max}} = \sqrt{\mathrm{S^2 - P^2}} \tag{3-27}$$

Finally, power converters normally have high operation efficiency, which would reduce the impact on the system losses and can be almost neglected from the planning point of view.

3.2. Mathematical model of the distribution network

The POMMP and POMMP2 methodologies are based on the initial definition of an existing base passive or active distribution network on which the microgrid will be planned or added. Furthermore, electric power simulations are required to compute dependent decision variables and characteristics of the steady-state operation of the microgrid along the planning horizon. Therefore, a steady-state mathematical model for quasi-dynamic power flow calculations of the base distribution network should be developed.

Initially, the models are based on a classic per-phase nominal-π equivalent circuit model for lines and the admittance (impedance) model for network calculations. Furthermore, the power flow equations can be re-written to include the active power charged or discharged by the ESS (Arefifar and Mohamed, 2014b) and represent the dual microgrid operation mode for each time step t in the planning horizon (Contreras *et al.*, 2018; Arefifar and Mohamed, 2014b).

3.2.1. Simulation of the grid-connected and islanded operation modes

Power flow equations can be re-written for considering ESS and the dual operation modes as it is shown in equations (3-28)-(3-29) and (3-30)-(3-31) for grid-connected and islanded modes, respectively.

$$\begin{split} \mathrm{P}_{\mathrm{fed}_t} + \sum_{n=1}^{\mathrm{N_{DG}}} \mathrm{P}_{\mathrm{DG}_{n,t}} \pm \sum_{n=1}^{\mathrm{N_{DS}}} \mathrm{P}_{\mathrm{DS}_{n,t}} - \sum_{n=1}^{\mathrm{N_{load}}} \mathrm{P}_{\mathrm{load}_{n,t}} = \cdots \\ \cdots = \sum_{i=1}^{\mathrm{N_{bus}}} \mathrm{V}_{i,t} \times \mathrm{V}_{j,t} \times \mathrm{Y}_{ij} \times \cos\left(\theta_{ij} + \delta_{t,j} - \delta_{t,i}\right), \forall j, t \end{split} \tag{3-28}$$

$$\begin{split} \mathrm{Q}_{\mathrm{fed}_t} + \sum_{n=1}^{\mathrm{N_{DG}}} \mathrm{Q}_{\mathrm{DG}_{n,t}} - \sum_{n=1}^{\mathrm{N_{load}}} \mathrm{Q}_{\mathrm{load}_t} = \cdots \\ \cdots = -\sum_{i=1}^{\mathrm{N_{bus}}} \mathrm{V}_{i,t} \times \mathrm{V}_{j,t} \times \mathrm{Y}_{ij} \times \sin\left(\theta_{ij} + \delta_{t,j} - \delta_{t,i}\right), \forall j, t \end{split} \tag{3-29}$$

$$\begin{split} \sum_{n=1}^{\mathrm{N_{DG}}} \mathrm{P}_{\mathrm{DG}_{n,t}} \pm \sum_{n=1}^{\mathrm{N_{DS}}} \mathrm{P}_{\mathrm{DS}_{n,t}} - \sum_{n=1}^{\mathrm{N_{lshed}}} \mathrm{P}_{\mathrm{lshed}_{n,t}} = \cdots \\ \cdots = \sum_{i=1}^{\mathrm{N_{bus}}} \mathrm{V}_{i,t} \times \mathrm{V}_{j,t} \times \mathrm{Y}_{ij} \times \cos\left(\theta_{ij} + \delta_{t,j} - \delta_{t,i}\right), \forall j, t \end{split} \tag{3-30}$$

$$\begin{split} \sum_{n=1}^{\mathrm{N_{DG}}} \mathrm{Q}_{\mathrm{DG}_{n,t}} - \sum_{n=1}^{\mathrm{N_{lshed}}} \mathrm{Q}_{\mathrm{lshed}_{n,t}} = \cdots \\ \cdots = -\sum_{i=1}^{\mathrm{N_{bus}}} \mathrm{V}_{i,t} \times \mathrm{V}_{j,t} \times \mathrm{Y}_{ij} \times \sin\left(\theta_{ij} + \delta_{t,j} - \delta_{t,i}\right), \forall j, t \end{split} \tag{3-31}$$

The subscripts fed, DG, DS and load describe the feeder, DGs, distributed ESS and loads in the network. The influence of the power exchange through the point of common coupling is represented by the feeder's power, and the $\mathrm{P}_{\mathrm{DS}_{n,t}}$ is positive during the discharging and

negative over the charging cycles. In islanded operation, the model can represent the possibility of load shedding, where $\mathrm{P_{lshed}}$ is the power demanded by the load shedding "lshed" as a possible demand managing strategy, $\sum_{n=1}^{N_{lshed}} \mathrm{P_{lshed}} < \sum_{n=1}^{N_{load}} \mathrm{P_{load}}$.
For solving the power flow problem, the selection of the slack-bus, PV bus and PQ bus will depend on the model of DERs and operation mode.

- PV buses - Dispatchable DERs
- PQ buses - Non-dispatchable DERs, ESS and load buses
- Slack bus - Selection according to the operation mode (grid-connected or islanded mode)

Dispatchable generation can be modeled as voltage-controlled unit, while non-dispatchable generation and ESS have the option to be defined either as PV or PQ buses depending on the power-electronic interface control and type of generator in the WT case. For example, directly coupled WT with induction machines consume reactive power and their output reactive power cannot be controlled, therefore they are typically model as PQ bus. Modern WT with doubly-fed induction generators, fully power electronic converter interconnected WT, and PV systems may fully control voltage and may be modeled as a typical PV bus generator from the perspective of the power flow. However, the control of the reactive power depends also on commercial considerations (as with traditional synchronous generators), and, usually, WT and PV generator owners try to operate at unity power factor to maximize their real power outputs (Glover *et al.*, 2012)[6]. Furthermore, in many countries, non-dispatchable DERs are normally required to operate with a fixed or limited range of power factors (fix VA rating) due to their limitations to control reactive power. Therefore, it has been assumed for the POMMP and POMMP2 methodologies that non-dispatchable DERs and ESS are modeled as PQ buses with known positive values for their output active and reactive power. The slack bus is assigned depending on the operation mode. In this manner, the slack bus is assigned in POMMP and POMMP2 methodologies following three architectures based on the possible operation modes: a fully grid-connected (networked) microgrid, a complete disconnected (networked) microgrid, and an islanded cluster in a networked microgrid.
The grid-connected and islanded conditions are described below, and the proposed strategy is depicted in Figure **3-17**.

1) **Grid-connected operation mode:** Slack bus is assigned to the main feeder of the microgrid. POMMP and PMMP2.

2) **Islanded operation mode:** Two different islanded conditions can be considered

[6]In some countries like Germany, it has been regulated a mandatory generation of a certain percentage of reactive power by DERs.

a. *Complete disconnected (networked) microgrid.* The slack bus is switched from the main feeder to the dispatchable DG with the highest capacity. POMMP and POMMP2.

b. *Individual disconnected cluster microgrid in a networked microgrid.* An individual cluster microgrid inside of the networked microgrid may operate in islanded mode. In this case, the dispatchable DG in the cluster operates as a slack bus. POMMP2.

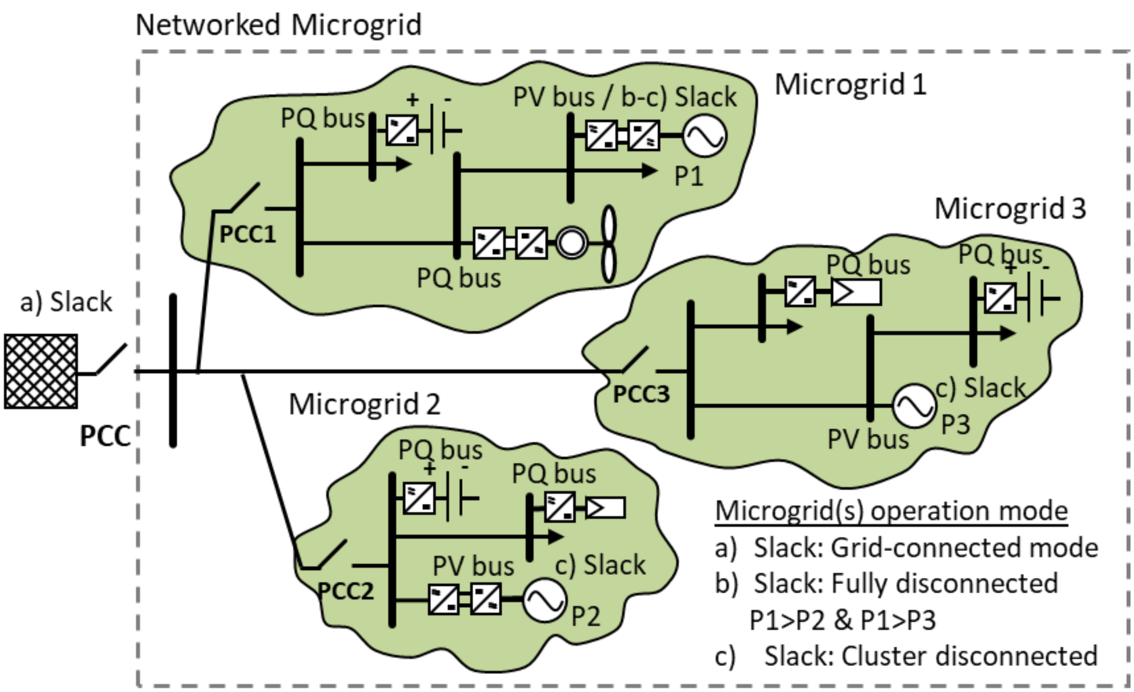

Figure 3-17.: Grid-connected and islanded mode power flow simulations

In view of the strategy, the distribution network model must admit iterative parameter adjustment and reconfiguration for quasi-dynamic power flow calculations. Some of these adjustments are, for example, the available active/reactive power of DERs at each time step, DERs' location, clustering of buses and topology reconfiguration.

3.2.2. Microgrid's network modeling for the topology planning

One of the main contributions of this research is found within the POMMP2 methodology, where it is proposed the holistic methodology for planning DERs and topology of microgrids simultaneously and under the paradigm of AS provision capability. From that perspective, the POMMP2 methodology is formulated as a bi-level optimization to define the microgrid's topology at a lower level and consider it for the whole metaheuristic optimization at the upper level (see Chapter 4). For that purpose, the microgrid's network is modeled at the

lower level based on **graph theory**, and a novel strategy to include a multilevel graph-partitioning technique for the optimal formation of clusters in the planning of networked microgrids is formulated by Contreras *et al.* (2020b) based on the previous work of us in (Cortes, Contreras and Shahidehpour, 2018).
The microgrid is then modeled as a graph $\mathrm{G_i(V,E)}$, where V (Vertices) represent the buses and E (Edges) the connection lines, Figure **3-18**. In POMMP2, V is always equal to the total number of buses $\mathrm{N_{bus}}$, while the connections E are established by the decision variables as it is described in Chapter 4.

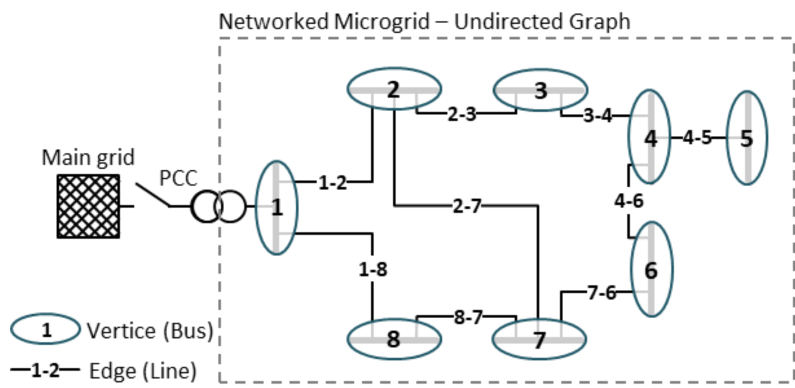

Figure 3-18.: Networked microgrid modeled as undirected graph

The networked microgrid is modeled as an undirected weighted graph, where in the example of Figure **3-18**, the graph has 8 vertices and 9 edges, where $\{1,2\} = \{2,1\}$. Furthermore, a weight is assigned to each edge of the graph that in the case of the microgrid can be resistance or length values for the lines.

$$\mathrm{V} = \{1,2,3,4,5,6,7,8\}$$
$$\mathrm{E} = \{\{1,2\},\{1,8\},\{2,3\},\{2,7\},\{3,4\},\{4,5\},\{4,6\},\{6,7\},\{7,8\}\}$$

The first goal of the network's model based on graphs it to facilitate tools for verifying a complete network (graph) connectivity during the topology forming step, since stand-alone buses are forbidden in the topology formation methodology. Hence, connectivity can be proved based on graph theory and existing computation functions[7]. In all cases, if G is an undirected graph, the graph is connected if all vertices are reachable, and at least one path between every two edges exists (Bender and Williamson, 2010).
The second goal of the microgrid's network graph model is to allow the implementation of graph partitioning methods for clusters and further microgrids topology formation (Cortes, Contreras and Shahidehpour, 2018). The basic idea is that the graph defined as a set of

[7]E.g. the Matlab function "conncomp(G)" returns the connected components of graph G as bins.

edges and vertices that it is possible for the graph defined as a set of edges and vertices to be segmented (partitioned), in a mathematical sense, into smaller sub-sets of vertices as well as edges. However, the graph partitioning is mostly understood as the partition of the vertices (buses) of the graph, and comprises a combinatorial optimization problem (Bichot and Siarry, 2013). The general partition is defined as (Bichot and Siarry, 2013):
If $\mathrm{G} = (\mathrm{V}, \mathrm{E})$ is a graph, and $\mathrm{P}_k = \{\mathrm{V}_1, \ldots, \mathrm{V}_k\}$ is a set of k sub-sets of V, P_k is a partition of G if

- No element of P_k is empty
- The elements of P_k are pairwise disjoint
- The union of the elements of P_k is equal to V

In the particular case of the POMMP2 methodology, once the graph is fully connected, **a multilevel graph partitioning method** (Lower-level optimization) is applied to find an optimal set of clusters (microgrids) that constitute the networked microgrid.

Multilevel graph partitioning method applied to POMMP2

The multilevel graph partitioning method was used by us in (Cortes, Contreras and Shahidehpour, 2018) for the loop-based topology planning in microgrids, and it is adapted for the POMMP2 methodology for the formation of clusters and further topology formation. The multilevel graph partitioning method aims to optimally group vertices together in order to deal with groups of vertices, rather than independent vertices for the partitioning of the graph (Bichot and Siarry, 2013). Therefore, the method is divided into three successive and well-distinct phases that act on the original graph $\mathrm{G}_0 = (\mathrm{V}, \mathrm{E})$. Furthermore, we proposed in (Cortes, Contreras and Shahidehpour, 2018) a novel iterative strategy to deal with the stochastic nature of the used multilevel graph partitioning technique and generate a so-called "suitable candidate clusters set". Furthermore, two criteria are considered for the POMMP2 methodology:

- The clusters are formed around a dispatchable generation unit. This means that the number of partitioning will be equal to the number of dispatchable units, and each cluster must contain at least one dispatchable generation unit on-site.
- Each cluster must contain a minimum amount of energy storage capacity. This is ensured with the proper energy resources sharing among clusters.

Multilevel graph partitioning phases is composed by three phases that are depicted in Figure **3-19** and described below.

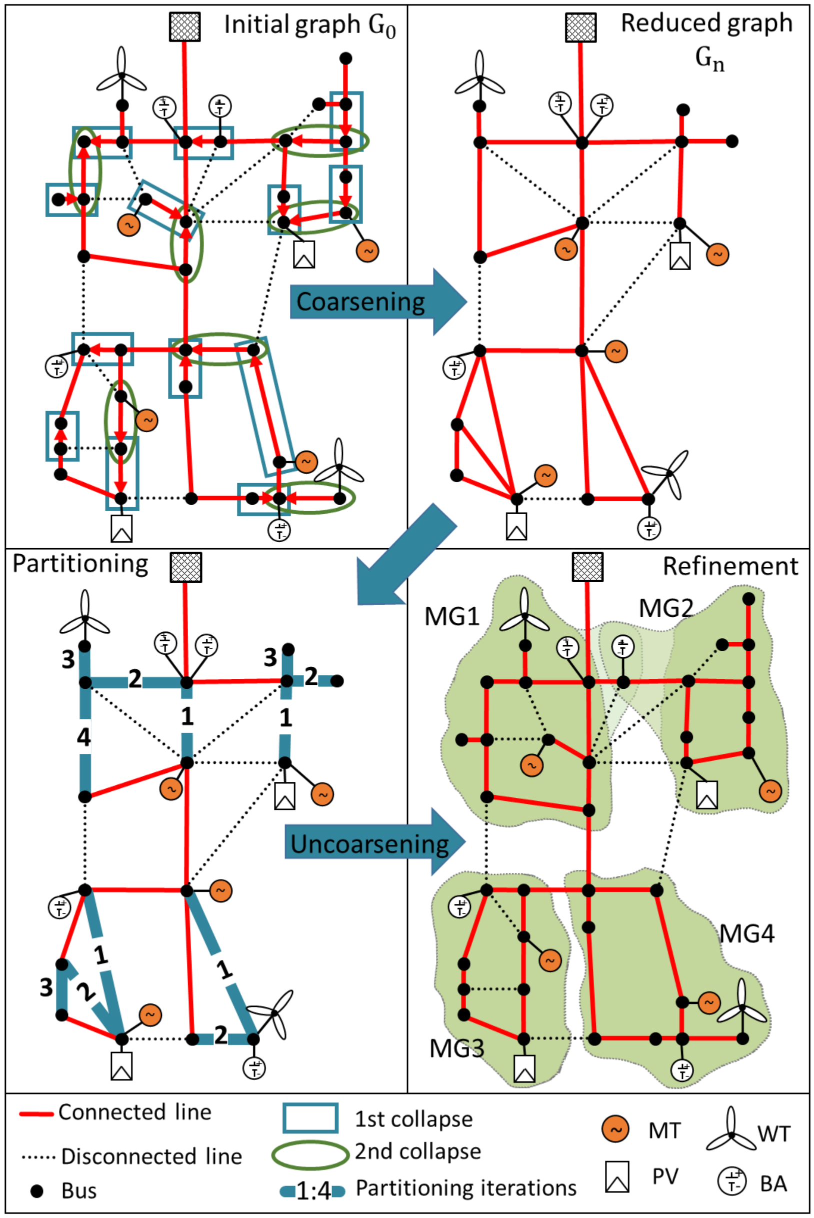

Figure 3-19.: Description of the multilevel graph partitioning strategy, adapted from Contreras *et al.* (2020b)

1) **Coarsening:**

The coarsening stage has the goal of reducing iteratively the size of the original graph by collapsing vertices and edges. The process uses the shortest edge machine (SEM) method (Cortes, Contreras and Shahidehpour, 2018) that modifies the heavy edge magine (HEM) principle. Accordingly, the process starts with a random selection of a vertice (bus) in the graph, which is subsequently matched with the closest adjacent bus in its neighborhood.

The vertices are then collapsed (merged) into a single vertice. Therefore, a graph G_i is generated in each iteration i so that each of its vertices represent a group of vertices from the previous graph G_{i-1} and its total number of vertices is lower. The iterative process ends when the graph is small enough and there is no further possible matching in the graph (Cortes, Contreras and Shahidehpour, 2018; Bichot and Siarry, 2013). As a result, if the number of iterations is n, the final family of graphs is $\{\mathrm{G}_0, \mathrm{G}_1, \ldots, \mathrm{G}_n\}$.

In (Cortes, Contreras and Shahidehpour, 2018), we proposed a strategy to discard infeasible coarsened cases where two vertices that contain generation resources are collapsed. In these cases, the coarsening phase would lead to a coarsened graph with fewer DERs resources and make this partitioning phase unfeasible. In the POMMP2 case, the strategy is maintained, with the difference that only the dispatchable units are considered for the discarding criteria.

2) **Partitioning:**

This phase generates a partition P_k^n of the coarcened graph G_n in k parts, where each part present a cluster. For that purpose, the coarsened graph G_n is partitioned by using the partitioning heuristic called "greedy graph growing partitioning (GGGP)" technique (Cortes, Contreras and Shahidehpour, 2018).

It is important to highlight that POMMP2 designates a cluster for at least one dispatchable unit. Accordingly, a partitioning cluster grows around a dispatchable DG bus based on GGGP, which selects an initial vertex and expands it to optimally cover a larger part of the coarsened graph G_n. The growing cluster strategy depends on the calculated gain for each cluster in each step. The gain is defined with the power mismatch ($\mathrm{mis}(\mathrm{V}_m)$) and the distance between vertices ($\mathrm{dis}(\mathrm{V}_j, \mathrm{V}_k)$), as it is described in equations (3-32) and (3-33) (Cortes, Contreras and Shahidehpour, 2018).

$$\mathrm{Gain}(\mathrm{V}_j) = \frac{|1 - \mathrm{mis}(\mathrm{V_m})|}{\mathrm{dis}\,\{\mathrm{V}_j, \mathrm{V}_k\}} \tag{3-32}$$

Where

$$\mathrm{mis}(\mathrm{V}_m) = \frac{\mathrm{GC}(\mathrm{V}_m) - \mathrm{D}(\mathrm{V}_m)}{\mathrm{D}(\mathrm{V}_m)} \tag{3-33}$$

Where GC is the distributed generation capacity and D is the peak load. The partitioning process ends when all the vertices are included in a cluster.

3) **Uncoarsening and refinement:**

In the uncoarsening and refinement phase, the partitioned graph P_k^n is projected back onto the initial graph G_0 following the same number of iterations n at the phase 1. Consequently, in each iteration the partition P_k^n of the graph G_n is first projected onto

G_{n-1}, which is refined based on the KL refinement algorithm (Cortes, Contreras and Shahidehpour, 2018; Bichot and Siarry, 2013). The refined partition becomes P_k^{n-1} of the graph G_{n-1}. The uncoarsening and refinement process is iteratively repeated for all the graphs G_i until the original graph is achieved, $i = 0$. In this phase a family of partitions is generated $\{P_k^n, \ldots, P_k^0\}$. The Kernighan–Lin (KL) refinement algorithm selects randomly a *frontier vertex* between adjacent parts of partitioned clusters, and evaluates the improvement of the partitioning through swapping a vertice between clusters *swap testing process*. The refinement is performed to achieve a better power balancing and guarantee a proper energy storage capacity distribution in the microgrids (Cortes, Contreras and Shahidehpour, 2018).

We proposed in (Cortes, Contreras and Shahidehpour, 2018) a normalization of the energy storage sharing capacity of the swap equation in order to avoid unnecessarily swaps in the uncoarsening phase. Furthermore, a strategy to identify feasible frontiers to avoid swaps that would disconnect certain parts of a cluster is implemented. In this case, a so-called "true frontier procedure" to evaluate a swap's feasibility is accomplished based on the connectivity evaluation by the Dulmage-Mendelsohn (DM) decomposition technique.

The main idea of the iterative strategy proposed by Cortes, Contreras and Shahidehpour (2018) for the clusters formation through multilevel graph partitioning technique is to iteratively find only suitable cases for the formation of clusters. For this two conditions were contemplated:

- Maximum power mismatch of all clusters in each iteration is the lowest value obtained so far.
- Minimum storage capacity per cluster is larger than or equal to a predefined value, e.g., at least one storage facility per cluster.

The first condition aims to exclude partitions that do not effectively balance the generation with the demand. The second condition removes partitions that do not efficiently distribute storage facilities among clusters. It is important to highlight that despite a partitioning cluster grows around a dispatchable DG bus based on GGGP, each cluster can include additional distributed generation (e.g. WT, PV) and must include at least one DS unit (see example in Figure **3-19**). The refinement strategy evaluates the mismatch power balance between the installed capacity of the whole generation matrix and the load demand per each cluster and assesses the energy storage resources sharing.
The iterative procedure proposed by Cortes, Contreras and Shahidehpour (2018) for clusters formation through multilevel graph partitioning technique is adapted for the lower-level optimization in the POOMP2 methodology. The iterative methodology evaluates a high number of clustering possibilities (1000 in this proposal) and finds a set of candidate clusters. In this case, the initial graph $mathrmG = G_0$ is modeled based on the microgrid definition

by the decision variable vector $\vec{x}$ (See Chapter 4) in the upper level of the methodology (See Chapter 5). Therefore, some configurations of the microgrid's topology from the decision variables configuration must be unfeasible for the clusters formation, which is also evaluated in the lower level. Hence, only suitable cases for the topology formation are projected from the lower-level to the upper-level for accomplishing the microgrid planning in the POMMP2 methodology.

3.3. Mathematical model of the uncertainties

It can be said that currently one of the most critical characteristics for the planning of ADN and microgrids is likely the presence of uncertainties. As we discussed before, there are present diverse sources of uncertainty in the operation of the microgrid. However, different authors agree in two main critical sources of uncertainty that must be included in modern analysis: Uncertainty in the generation from renewable resources such as WT and PV generation, and uncertainty in the load demand. Consequently, those two sources have been modeled and included as part of the POMMP and POMMP2 methodologies.

It was also discussed the existence of different uncertainty modeling techniques, whose suitability depends mainly on the accessibility to historical data of the uncertain variable (Aien *et al.*, 2016). Currently, the increasing interest in the integration of renewable technologies based on wind and solar generation, and the expansion of smart grid measuring and communication technologies has led to expand and improve the measuring and recording data systems and networks for key climatic and electric variables. Therefore, it is considered in this doctoral thesis that time series for uncertain variables such as wind speed, solar irradiation and load demand are available since it is expected that in future the accessibility to historical data is not a common issue.

In this context, the probabilistic approach was chosen as technique to model uncertainty for the POMMP and POMMP2 methodologies. The technique was selected based on different good results in the literature, such as in (Arevalo *et al.*, 2017; Arefifar and Mohamed, 2014b), which have been also reaffirmed as a simple and powerful strategy with recent research (Machado *et al.*, 2019). In this section, the main characteristics of the probabilistic uncertainty modeling for the wind generation, solar generation and load demand will be described.

3.3.1. Probabilistic approach for uncertainty modeling

The probabilistic approach is based on probability and stochastic process theory[8], since the probabilistic techniques aim to determine the statistical properties of the uncertain variables

[8] The detail of this theory is left out of the scope of this dissertation, and can be consulted in references such as (Papoulis and Pillai, 2002; Thomopoulos, 2013).

using the probability distribution functions (PDF) (Ehsan and Yang, 2019; Xiang *et al.*, 2016).
The PDFs of the input random variables need to be estimated from the respective historical data of uncertain parameters. Thus, in general terms, the probabilistic modeling technique consists of analyzing historical data (e.g. data of weather and load for a certain time window and time steps), fitting a PDF for each time step, and then, sampling the random variables, which will be the input expected values for the mathematical model (Park *et al.*, 2009), Figure **3-20**.

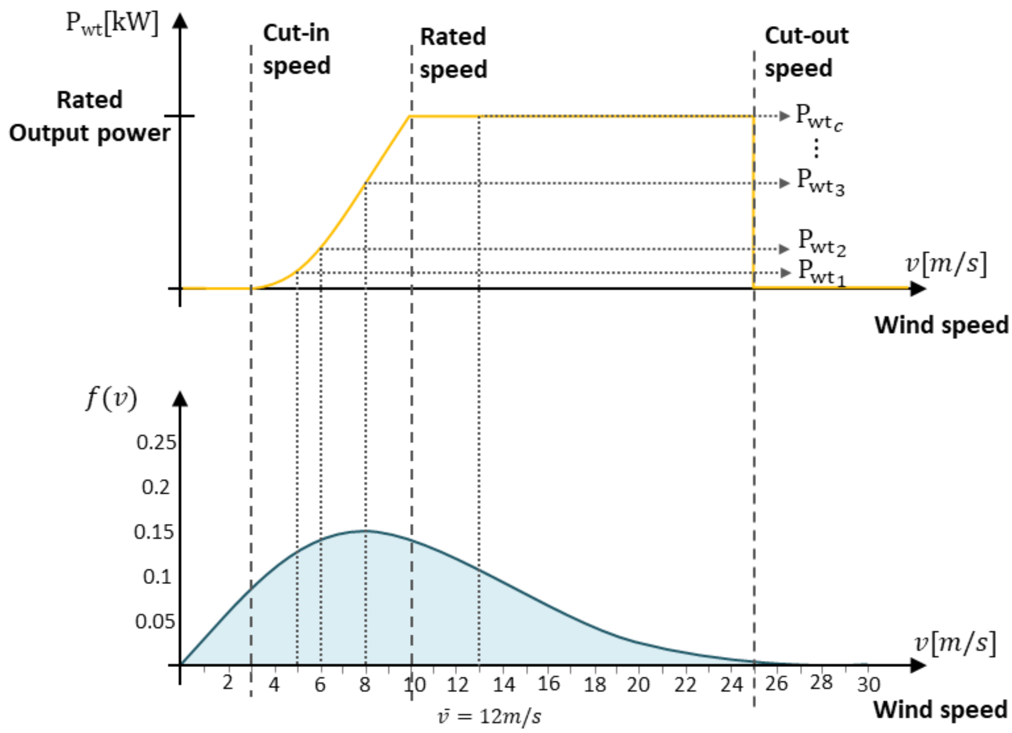

Figure 3-20.: Example of the relationship between the probabilistic wind speed model and the wind turbine power output model, adapted from Park *et al.* (2009)

In terms of the sampling strategy, probabilistic techniques can be classified into numerical and analytical techniques (Ehsan and Yang, 2019; Aien *et al.*, 2016). For the adopted probabilistic uncertainty modeling technique in POMMP and POMMP2 methodologies, the Monte Carlo Simulation (MCS) numerical technique is used for estimating the PDF of the uncertain parameters. This was chosen since it is one of the most common, adaptable and simplest stochastic methods. Furthermore, MCS is a system-size independent approach and can be used when the system is highly nonlinear, complex, or has many uncertain variables (Aien *et al.*, 2016). One of the disadvantages is the high computational burden, which becomes a problem for large power systems or particular case studies in the microgrids. However, it is confirmed in this research that average size microgrid planning (e.g. 37, 69

buses) can be feasibly solved with current computational technologies and the POMMP and POMMP2 planning methodologies.
The approach is described below based on the convenient explanation offered by Aien *et al.* (2016).

Probabilistic approach based on iterative MCS method

In the probabilistic approach, consider that $y = f(\vec{x})$ is a multivariate function where $\vec{x} = [x_1, x_2, x_3, \cdots, x_n]$ is the vector of uncertain input random variables. It is considered that the historical data of the random variable is known and the PDF of the variable can be defined based on those time series. Afterward, MCS is used to obtain the PDF of y or the expected output variable (e.g. wind speed, solar irradiation, percentage of load demand). The steps of the iterative method for the planning problem is described below (Aien *et al.*, 2016; Soroudi, 2014):

Step 1. Obtain and arrange historical data for the random variable: wind speed, solar irradiation, load demand. The accuracy of the modeling technique is directly affected by the number of data (Arefifar and Mohamed, 2014b). Furthermore, the random variables are independent among them.

Step 2. Define time series for each random variable and time step of the planning horizon. The time step is defined as one hour (1h) for POMMP and POMMP2, while typical days of 24 hours are defined along the planning horizon.

Step 3. Find the parameters of a fitting PDF for the time series of the random variable. Weibull, Log-normal, Beta, and normal PDF have been widely studied as suitable PDFs for the required random variables[9].

Step 4. MCS iterative method for each random variable and time step

- Step 4.1 Set MCS counter at c=1
- Step 4.2 Randomly generate a sample for the vector $\vec{x}$ using the PDF of each component x_i .
- Step 4.3 Calculate y_c assuming that $\vec{x} = \vec{x}_c$ as $y_c = f(x_c)$
- Step 4.4 Calculate the expected value of y as $\mathrm{E}(y) = \frac{\sum_c y_c}{c}$
- Step 4.5 Maximum number of iterations is met? End, else set counter c=c+1 and return to step 4.2.

Step 5. end

[9](Arevalo *et al.*, 2017; Arefifar and Mohamed, 2014b; Zidan *et al.*, 2013; Atwa *et al.*, 2011; Salameh *et al.*, 1995).

For the proposed planning methodologies in this dissertation, four traditional PDF functions were reviewed: Weibull for wind speed, Beta or log-normal for solar irradiance and normal for load demand. The PDF equations are shortly described below while the time series, histograms and PDF fitting plots for the used time-series in the case studies can be consulted in Appendix B. Currently, numerical computing tools such as Matlab have PDF functions and PDF's parameters fitting functions based on Chi-square and Kolmogorov-Smirnov goodness of fit methods.

3.3.2. Probability density functions for stochastic generation and load

Wind speed and Weibull distribution

It is well known that the Weibull PDF fits normally well for the wind speed stochastic behavior. The Weibull distribution is a continuous probability distribution with two-parameters as in equation (3-34) (Kwasinski *et al.*, 2016).

$$y = f(x; \lambda, k) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} \exp^{-(x/\lambda)^k} \quad \text{for} \;\; x \geq 0 \tag{3-34}$$

Where $x = v$ is the random variable of wind speed, and k and λ are the two parameters of the Weibull distribution. $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter of the distribution. A related PDF is the Rayleigh probability distribution that is the Weibull distribution when $k = 2$ and the Rayleigh moda $\sigma = \lambda/\sqrt{2}$ (Arevalo *et al.*, 2017; Kwasinski *et al.*, 2016).

Solar irradiation and Log-normal distribution

Different PDF have been tried to represent the stochastic behavior of solar irradiation. One of them is the Log-normal distribution (Arevalo *et al.*, 2017), which is a PDF or a random variable whose logarithm is normally distributed.
In probability theory, a log-normal distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed. The PDF is given in equation (3-35) (Thomopoulos, 2013).

$$y = f(x; \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left[\frac{-(\log x - \mu)^2}{2\sigma^2}\right]^{k-1} \quad \text{for} \;\; x > 0 \tag{3-35}$$

Where $x = E_{\mathrm{g}}$ is the solar irradiation, μ is the mean of logarithmic values and σ is the standard deviation of logarithmic values. Notice that if x follows the log-normal distribution with parameters μ and σ, then $\log(X)$ follows the normal distribution with mean μ and standard deviation σ. Furthermore, because the random variable takes only positive real values in the log-normal PDF, zero values of the solar irradiation must be set it up as representative small values.

Solar irradiation and Beta distribution

Depending on the time series of solar irradiation, Beta PDF can fit better than the other two-parameters PDFs (Gazijahani and Salehi, 2017; Salameh *et al.*, 1995). Beta function is defined by equation (3-36).

$$y = f\left(x;\alpha,\beta\right) = \frac{1}{B(\alpha,\beta)} \cdot x^{\alpha-1}\left(1-x\right)^{\beta-1} \quad \text{for} \;\; 0 \leq x \leq 1 \tag{3-36}$$

Where

$$B(\alpha,\beta) = \int_0^1 t^{\alpha-1}\left(1-t\right)^{\beta-1} dt = \frac{\Gamma(\alpha)\Gamma(\alpha)}{\Gamma(\alpha+\beta)} \tag{3-37}$$

The $B(\alpha,\beta)$ is the beta function, a normalization constant to guarantee that the total probability is 1. $x = E_{\mathrm{g}}$ is the solar irradiation realization that should be defined in the interval $[0,1]$ and the function has two positive shape parameters $\alpha > 0$ and $\beta > 0$.

Load demand and normal distribution

The normal distribution is a typical continuous probability distribution and it has been used by several authors to model the stochastic behavior of the electric load demand (Gazijahani and Salehi, 2017). The normal distribution is given by equation (3-38).

$$y = f\left(x;\mu,\sigma\right) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[\frac{-\left(x-\mu\right)^2}{2\sigma^2}\right] \quad \text{for} \;\; x \in \mathbb{R} \tag{3-38}$$

Where $x = \mathrm{P}_{\mathrm{load}}$ is the percentage of load demand (or load demand in p.u.), μ is the mean or expectation of the distribution and σ is the standard deviation. Notice that σ^2 is the variance of the distribution.

3.4. Mathematical model of the operation

One of the main implications of the integration of DERs together with powerful control architectures in microgrids is not only to ensure safe and reliable operation of the system but also to provide the capability of active management for optimal operation. Hence, operation conditions are not anymore an insulated task from the planning stage, since the active operation benefits overcome the ones achieved with a traditional fit-and-forget planning technique. Furthermore, the presence of non-dispatchable generation units introduces a non-controllable generation capacity, whose potential impact can be exploited only from the optimal operation of the system based on forecast and uncertainty models.

Therefore, two main operation strategies:

- Operation between dispatchable and non-dispatchable units, and
- Operation strategy of ESS,

are modeled as part of the POMMP and POMMP2 methodologies to accomplish operation requirements in terms of the internal power balance of the microgrid, and AS provision enhancement (spinning reserve, non-spinning reserve, and frequency up- and down-regulation) from power reserve capacity. The operation strategies for the proposed methodologies are integrated from the definition of the optimization problem, which are explained in detail in Chapter 4, while the mathematical models are presented in this section.
The operation strategies here proposed are evaluated for the POMMP and POMMP2 methodologies at each time step t along the planning horizon. However, control and operation are in practice based on control signals that are received, compared and processed to respond under diverse time windows. These signals can have different natures, for example, frequency signals for power balancing, or economical signals for the provision of services, and control architectures can accordingly become considerably complex.
New proposals suggest implementing bi-level optimization techniques to involve control results in the optimization problem (Li *et al.*, 2017). However, this strategy, although recognized by us, was left out of the scope of this research since it adds a considerable high computational burden and it is considered that immediate steps in the microgrid planning research roadmap must focus on other characteristics that we intend to tackle in this dissertation. In this way, operation characteristics are in principle included in the planning methodologies through the mathematical models below, constraints in the optimization problem and the planning strategy.

3.4.1. Operation between dispatchable and non-dispatchable units

The main idea in the expected operation strategy for a microgrid with a mixed generation matrix was described for the dispatchable generation in Section 3.1. Correspondingly, the main criteria is that renewable non-dispatchable generation must operate as grid following generation, while dispatchable units must operate as a grid forming generation. Therefore, for each time-step in the planning horizon, the power balanced is constrained in such a way that dispatchable DGs provide the required mismatch power to guarantee a balance between load and generation at any time. The remaining available generation power is considered reserve power for participating in the electric market. The operation characteristic is described in the constraints of the optimization problem.
In that vein, the energy balance in islanded mode includes generated and stored power, demanded power and power losses. For the islanded operation simulation, the slack bus is switched from the main feeder to the largest dispatchable unit of the fully connected

networked microgrid or each cluster in the microgrid (Section 3.2). Finally, power flow is used to calculate the mismatch power for each time-step t. The constraint is given by equation (3-39).

$$\sum_{t=1}^{n_t}\sum_{j=1}\mathrm{PI}_{\mathrm{DG}_{j,mg,t}} = \sum_{t=1}^{\mathrm{n}_t}\left(\sum_{l}\mathrm{PI}_{\mathrm{load}_{l,mg,t}} + \mathrm{PI}_{\mathrm{loss}_{mg,t}} \pm \sum_{b}\mathrm{PI}_{\mathrm{DS}b,mg,t}\right), \quad \forall \quad mg, j, b, t \tag{3-39}$$

Where $\mathrm{PI}_{\mathrm{DG}_{j,mg,t}}$ is the total power generated by the DGs for the microgrid and cluster microgrid mg in islanded mode, $j = (g \cup c)$ is the set of technologies g, discrete sizing capacity generation technologies WT and MT, and c continuous sizing capacity generation technology PV; $\mathrm{PI}_{\mathrm{load}_{l,mg,t}}$ is the demanded load in the microgrid mg; $\mathrm{PI}_{\mathrm{loss}_{mg,t}}$ are the power losses in the microgrid mg; and $\mathrm{PI}_{\mathrm{DS}b,mg,t}$ is the charging or discharging power delivered by the set of batteries system b.
With this constraint, the rated capacity of the dispatchable units is optimally sized to ensure power mismatch during a continuous islanded operation of the networked MG, as well as to limit the oversize of the DERs in the system due to the reserve capacity optimization goal. Clearly, for each time step t in islanded mode, the power delivered by the dispatchable units should negatively or positively compensate the mismatch power in the microgrid.

3.4.2. Operation strategy of the ESS

ESS, or battery systems for POMMP and POMMP2, are a key component for the microgrid's operation. Batteries are a flexible component that can offer a wide range of control and active management strategies.
In the POMMP and POMMP2 methodologies, the operation strategy for batteries was defined to operate in charging cycle during low demand time to guarantee SOC=1 at the end of the period, and operate in discharging cycle during high demand time and delivering power depending on market signals for providing reserve power flow in the microgrid and AS to the main grid (Contreras *et al.*, 2019).
Accordingly, the mathematical model in the POMMP and POMMP2 methodologies incorporates binary indirect decision variables to simulate the operation control of the C/D cycle of BA (Contreras *et al.*, 2019). Hence, in grid-connected operation mode, the binary operation variables $\mathrm{b}_{\mathrm{RDn}_{m,d,h}}$, for selling frequency down-regulation, and $\mathrm{b}_{\mathrm{Aux}_{m,d,h}}$, for supplying AS, are used (Contreras *et al.*, 2019; Cardoso *et al.*, 2017). Furthermore, C/D cycles are commanded by a demand management strategy based on the Microgrid's power demand-generation rate in grid-connected operation mode and islanded operation mode. This is shown from equation (3-40) to (3-45). For this purpose, the mathematical model of the batteries based on the SOC defined with equations (3-21) and (3-22) are modified as follows (Contreras *et al.*, 2019).
k represents a battery system in the microgrid, SOC_k is the battery state of charge, MSOC_k is the maximum charge (SOC=1), MDOD_k is the maximum depth of discharge (minimum

SOC), η_{ba_k} is the battery self-discharge coefficient, $\mathrm{E}_{\mathrm{ba}_k}$ is the available battery energy [kWh], and $\mathrm{C}_{\mathrm{ba}_k}$ is the battery rated capacity [kWh].

$$\mathrm{SOC}_k\left(t+1\right) = \mathrm{SOC}_k\left(t\right)\left(1-\eta_{\mathrm{ba}_k}\right) \pm \frac{\mathrm{E}_{\mathrm{ba}_k}}{\mathrm{C}_{\mathrm{ba}_k}} \tag{3-40}$$

$$\mathrm{E}_{\mathrm{ba}_k}\left(\mathrm{SOC}_k\right) = \begin{cases} \mathrm{P}^{\mathrm{ch}}_{\mathrm{ba}_k} \cdot \eta_{\mathrm{ch}_k} & \text{if } \mathrm{b}_{\mathrm{ch}_{m,d,h}} = 1 \\ \\ -\mathrm{P}^{\mathrm{dch}}_{\mathrm{ba}_k} \cdot 1/\eta_{\mathrm{dch}_k} & \text{if } \mathrm{b}_{\mathrm{dch}_{m,d,h}} = 1 \end{cases} \tag{3-41}$$

$\mathrm{P}^{\mathrm{ch}}_{\mathrm{ba}_k}$, $\mathrm{P}^{\mathrm{dch}}_{\mathrm{ba}_k}$ and $\eta_{\mathrm{ch,dch}_k}$ represent the battery k charging/discharging input/output power and efficiency, respectively. The binary variables for commanding the *ch* and *dch* cycles are defined as in equations (3-42)-(3-46):

Grid-connected mode:

$$\mathrm{b}_{\mathrm{ch}_{m,d,h}} = 1 \quad \text{if} \begin{cases} \mathrm{SOC}_k\left(t+1\right) & \leq \mathrm{MSOC} & \text{AND} \\ \mathrm{b}_{\mathrm{RDn}_{m,d,h}} & = 1 & \text{OR} \\ \mathrm{b}_{\mathrm{Bpk}_{m,d,h}} & = 1 & \end{cases} \tag{3-42}$$

$$\mathrm{b}_{\mathrm{dch}_{m,d,h}} = 1 \quad \text{if} \begin{cases} \mathrm{SOC}_k\left(t+1\right) & \geq \mathrm{MDOD} & \text{AND} \\ \mathrm{b}_{\mathrm{Aux}_{m,d,h}} & = 1 & \text{OR} \\ \mathrm{b}_{\mathrm{Bpk}_{m,d,h}} & = 0 & \end{cases} \tag{3-43}$$

Islanded mode:

$$\mathrm{b}_{\mathrm{ch}_{m,d,h}} = 1 \quad \text{if} \begin{cases} \mathrm{SOC}_k\left(t+1\right) & \leq \mathrm{MSOC} & \text{AND} \\ \mathrm{b}_{\mathrm{Bpk}_{m,d,h}} & = 1 & \end{cases} \tag{3-44}$$

$$\mathrm{b}_{\mathrm{dch}_{m,d,h}} = 1 \quad \text{if} \begin{cases} \mathrm{SOC}_k\left(t+1\right) & \geq \mathrm{MDOD} & \text{AND} \\ \mathrm{b}_{\mathrm{Bpk}_{m,d,h}} & = 0 & \end{cases} \tag{3-45}$$

Where $\mathrm{b}_{\mathrm{Bpk}_{m,d,h}}$ is defined in equation (3-46).

$$\mathrm{b}_{\mathrm{Bpk}_{m,d,h}} = \begin{cases} & \mathrm{P}_{\mathrm{DG}_{m,d,h}} - \left(\mathrm{P}_{\mathrm{load}_{m,d,h}} + \mathrm{P}_{\mathrm{loss}_{m,d,h}}\right) > 0 \\ 1 & \text{OR} \\ & \mathrm{P}_{\mathrm{load}_{m,d,h}} <= 1.2 \times \text{MIN } \mathrm{P}_{\mathrm{load}} \\ \\ & \mathrm{P}_{\mathrm{DG}_{m,d,h}} - \left(\mathrm{P}_{\mathrm{load}_{m,d,h}} + \mathrm{P}_{\mathrm{loss}_{m,d,h}}\right) \leq 0 \\ 0 & \text{OR} \\ & \mathrm{P}_{\mathrm{load}_{m,d,h}} <= 0.8 \times \text{MAX } \mathrm{P}_{\mathrm{load}} \end{cases} \tag{3-46}$$

Thus, $\mathrm{b}_{\mathrm{RDn}_{m,d,h}}$ and $\mathrm{b}_{\mathrm{Aux}_{m,d,h}}$ change their state depending on the market and the main network operator simulation proposed and explained in next Section 3.5. In equation (3-46), $\mathrm{P}_{\mathrm{DG}_{m,d,h}}$ is the active power generated by the DG [kW], $\mathrm{P}_{\mathrm{load}_{m,d,h}}$ is the active power demanded by the load [kW], and $\mathrm{P}_{\mathrm{loss}_{m,d,h}}$ are the power losses [kW].

3.5. Mathematical model of economic framework

The economic framework represents a complex issue for the planning problem. This is due to the difficulty of forecasting future new market conditions in the medium or long term and sometimes the difficult access to historical data of the market's behavior. The challenge is even bigger when it is needed to model services market conditions and consider DERs in the microgrid. Therefore, for the POMMP and POMMP2 methodologies, the strategy proposed by Cardoso *et al.* (2017) for the DER-CAM planning tool was adopted as a reference for the proposal of the economic model for planning in POMMP and POMMP2 (Contreras *et al.*, 2019; Peñaranda *et al.*, 2019).

3.5.1. Model for the participation strategy on the AS markets

The strategy proposed together with the research by Peñaranda *et al.* (2019) aims to define signals for the decision on the utilization of the available residual power in the microgrid at each time-step along the planning horizon. For that purpose, four key assumptions were defined.

- The microgrid is modeled as a controlled generation or demand entity by the upstream system operator (TSO or DSO). This means that, from the operator point of view, it is not visible the type of generator within the microgrid that is providing reserve power for AS procurement. Hence, the capacity for bidding AS provision is evaluated during each time step based on the residual power after power dispatch inside of the microgrid.

- It is assumed that the microgrid acts mainly as a price-taker in the AS markets that can participate along the planning horizon. For that purpose, the market-clearing price is considered a good indicator of a successful bid. Under this presumption, it is considered that the residual capacity allocation during each time-step for participation in AS markets is always conferred after bided.

- Resulting clearing price for each AS market represents the requirements of the electric market to ensure the reliable and secure operation of the power system.

- It is considered that the requirements for AS provision variate among electric markets. Therefore, conditions such as response time to a service request upon a successful bid, a minimum size of the resource to participate in the market, and the minimum length of the bid duration should be taken into account. It is assumed that the microgrid's assets can respond to the AS market required times, while the minimum capacity and bid duration are considered as part of the planning model.

The proposed strategy uses as reference historic data of market-clearing prices for the procurement of different AS. Thus, different market-clearing prices are compared for each time

step and the highest price is chosen for the microgrid's bid depending on its power balance and total capacity. Therefore, the revenue from the bid in the selected AS market and microgrid's market participation is calculated based on the market-clearing price and the bid duration.
Considering the strategy above, four different electric markets can be considered: Sale of electricity, spinning reserve, non-spinning reserve and frequency regulation (up and down). An example of the comparative strategy over the reference historical data is shown in Figure **3-21** (Peñaranda *et al.*, 2019; Contreras *et al.*, 2019).

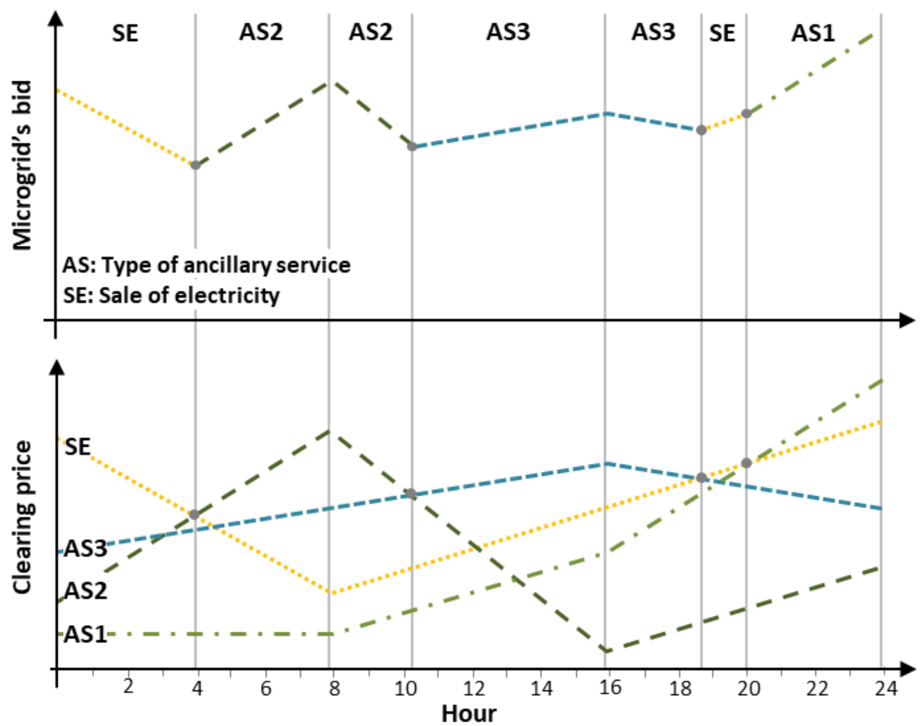

Figure 3-21.: Overview of the strategy for bidding in electric and AS market over clearing prices comparison, adapted from Peñaranda Bayona and Mosquera Duarte (2018)

Under this premise, the capacity allocation is determined by POMMP and POMMP2 during each time step based on the available microgrid's residual power for participation in AS markets. The maximum clearing price is chosen with equation (3-47).

$$\mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{MAX}\ \left(\mathrm{T}_{\mathrm{Ex}_{m,d,h}}, \mathrm{S}_{\mathrm{MCP}_{m,d,h}}, \mathrm{NS}_{\mathrm{MCP}_{m,d,h}}, \mathrm{R}_{\mathrm{UpMCP}_{m,d,h}}, \mathrm{R}_{\mathrm{DnMCP}_{m,d,h}}\right) \quad [\$] \tag{3-47}$$

Where $\mathrm{T}_{\mathrm{arMAX}_{m,d,h}}$ is the maximum rate between different services to be exported to the grid [\$], $\mathrm{T}_{\mathrm{Ex}_{m,d,h}}$ is the regulated tariff for electricity [\$/kWh] and $\mathrm{S}_{\mathrm{MCP}_{m,d,h}}$, $\mathrm{NS}_{\mathrm{MCP}_{m,d,h}}$,

$\mathrm{R}_{\mathrm{UpMCP}_{m,d,h}}$, and $\mathrm{R}_{\mathrm{DnMCP}_{m,d,h}}$ are the regulated tariffs for spinning reserve, non-spinning reserve, and frequency up- and down-regulation, respectively, in $[\$/kWh]$. Afterwards, binary values are assigned to the associated binary variables of each one of the possible AS markets in which the Microgrid optimally could participate along the planning horizon (Contreras *et al.*, 2019). A binary decision variable is assigned as 1 if it is possible to bid for a particular AS market or 0 if a participation is not possible (Peñaranda *et al.*, 2019; Contreras *et al.*, 2019). Correspondingly, five binary variables are defined:

- $\mathrm{b}_{\mathrm{Aux}_{m,d,h}}$: bid for selling of electricity to the wholesale market.
- $\mathrm{b}_{\mathrm{S}_{m,d,h}}$: bid for spinning reserve AS.
- $\mathrm{b}_{\mathrm{NS}_{m,d,h}}$: bid for non-spinning reserve AS.
- $\mathrm{b}_{\mathrm{RUp}_{m,d,h}}$: bid for frequency up-regulation AS.
- $\mathrm{b}_{\mathrm{RDn}_{m,d,h}}$: bid for frequency down-regulation AS.

The binary conditions for the provision of an AS are defined in equations (3-48) to (3-53) for each time step along the planning horizon

$$\mathrm{b}_{\mathrm{Aux}_{m,d,h}} = \begin{cases} 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{S}_{\mathrm{MCP}_{m,d,h}} \\ 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{NS}_{\mathrm{MCP}_{m,d,h}} \\ 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{R}_{\mathrm{UpMCP}_{m,d,h}} \\ 0 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{R}_{\mathrm{DnMCP}_{m,d,h}} \\ 0 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{T}_{\mathrm{Ex}_{m,d,h}} \end{cases} \tag{3-48}$$

$$\mathrm{b}_{\mathrm{S}_{m,d,h}} = \begin{cases} 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{S}_{\mathrm{MCP}_{m,d,h}} \\ 0 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} \neq \mathrm{S}_{\mathrm{MCP}_{m,d,h}} \end{cases} \tag{3-49}$$

$$\mathrm{b}_{\mathrm{NS}_{m,d,h}} = \begin{cases} 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{NS}_{\mathrm{MCP}_{m,d,h}} \\ 0 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} \neq \mathrm{NS}_{\mathrm{MCP}_{m,d,h}} \end{cases} \tag{3-50}$$

$$\mathrm{b}_{\mathrm{RUp}_{m,d,h}} = \begin{cases} 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{R}_{\mathrm{UpMCP}_{m,d,h}} \\ 0 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} \neq \mathrm{R}_{\mathrm{UpMCP}_{m,d,h}} \end{cases} \tag{3-51}$$

$$\mathrm{b}_{\mathrm{RDn}_{m,d,h}} = \begin{cases} 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{R}_{\mathrm{DnMCP}_{m,d,h}} \\ 0 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} \neq \mathrm{R}_{\mathrm{DnMCP}_{m,d,h}} \end{cases} \tag{3-52}$$

$$\mathrm{b}_{\mathrm{TEx}_{m,d,h}} = \begin{cases} 1 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} = \mathrm{T}_{\mathrm{Ex}_{m,d,h}} \\ 0 & \text{if} \quad \mathrm{T}_{\mathrm{arMAX}_{m,d,h}} \neq \mathrm{T}_{\mathrm{Ex}_{m,d,h}} \end{cases} \tag{3-53}$$

Accordingly to Cardoso *et al.* (2017), traditionally AS bids must ensure at least 1h in all AS markets, and AS signals response to a request may be needed within seconds for frequency regulation markets, or within few minutes for spinning and non-spinning reserve markets. As it was mentioned above, it is assumed that microgrids can respond within required times based on the stored energy and allocation of dispatchable resources. However, the bid duration and capacity are constrained as part of the optimization problem formulation. For example, non-spinning reserve in the CAISO market, an ISO in the USA, must be able to respond within 10 minutes of being requested and must be provided for at least 2 hours, while the same AS in the ERCOT market, also an ISO in the USA, must respond within 30 minutes and run for at least 1 hours (Cardoso *et al.*, 2017; Zhou *et al.*, 2016). These requirements can be set up as requirements in the constrained planning optimization problem.

3.5.2. Model for the value of investments over time

Additionally to the strategy and mathematical model described above, typical economical concepts are used to model the economic factors contributing to the economic objective functions of the optimization problem. More specifically, the models must consider the time value of money along the entire time of the study.

For that purpose, cash flow concepts and fix economic factors used in the profit objective function such as capital cost, installation cost, and depreciation should be considered overtime. Hence, investment costs are annualized using an annuity rate that depends on the compounded interest rate and technology lifetime, equation (3-54) (Cardoso *et al.*, 2017).

$$\mathrm{An}_i = \frac{\mathrm{IR}}{\left(1 - \frac{1}{(1+\mathrm{IR})^{\mathrm{Lt_i}}}\right)} \quad \forall \; i \tag{3-54}$$

Therefore, equation (3-54) determines the annualized capital cost of DER investments with an interest rate IR, and lifetime Lt of the DER technology i.

3.6. Planning strategy for the POMMP and POMMP2 methodologies

One of the stages in the solution of the planning problem is the strategy stage. The definition of the optimization problem and planning "strategy" by itself. As part of the strategy, some important generalities should be defined, as the planning type, time-scale/planning horizon and number of stages (Ehsan and Yang, 2019).

Most of the features here described have been already described along with the definition of the mathematical models for the POMMP and POMMP2 methodologies. However, these main characteristics are specifically described in this section.

Type of planning

POMMP and POMMP2 methodologies have been defined for planning MV utility or networked microgrids over a base case. Consequently, the main type of planning of the methodologies is the transformation of passive distribution networks into microgrids, expansion and clustering of existing ADN or reinforcement of existing microgrids.
The planning of new microgrids is also possible. However, in this case, it would be necessary to pre-define a base case depending on the context and likely a known benchmark that offers similar conditions for the desired architecture of the microgrid.

Time-scale and planning horizon

According to Seifi and Sepasian (2011), power systems planning studies are traditionally considered withing periods between 1 to 10 years, while Ehsan and Yang (2019) describe short-term planning between 1 to 5 years, medium-term planning between 5 to 15 years and long-term planning between 15 to 20 years. Regarding this point, one relevant fact is the big change in the planning paradigm, since the planning of conventional power systems usually required large-scale infrastructure projects with long deployment and construction times[10]. Conversely, microgrids would give rise to more flexible transformation and transitional strategies, where shorter planning horizon are likely more appropriated.
Modern planning strategies are being proposed, such as the one proposed by Hinker *et al.* (2018) to properly use the implicit adaptability, standardization and scalability features of DERs for local distribution network architectures. The planning methodology here proposed considers a concept called "bridging systems" that indicates that the conditions along the planning path for achieving a final optimal system change along the time. Consequently, the strategy proposes intermediate steps of the investment/expansion overall planning problem to improve supply systems stage by stage, Figure **3-22**.
Therefore, and considering proposals such as in (Cardoso *et al.*, 2017; Arefifar and Mohamed, 2014b), the chosen default planning horizon for the POMMP and POMMP2 methodologies is one year. Nonetheless, adaptations in the planning horizon are possible considering proper interest rates and demand increase factors for the uncertainty models.
A second important characteristic is the planning horizon, which is the time steps for the analysis. For the proposed methodologies, the strategy of Cardoso *et al.* (2017) for DER-CAM was adapted. Therefore, three day-types: weekday, weekend day and month's peak

[10]Consider the reader, for example, the construction time for the Itaipu hydroelectric power plan in South America needed around 10 years (1974-1985) for its construction `https://www.itaipu.gov.py/en/nossahistoria`.

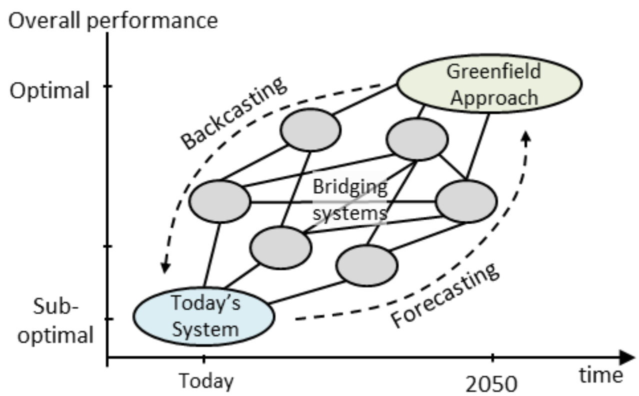

Figure 3-22.: Vision of transition paths to final greenfield optimality, adapted from Hinker *et al.* (2018)

demand day, are modeled with 24 hours for each month of the year to constitute the planning horizon, Table **3-4**

Table 3-4.: Planning horizon and time steps for three typical days in the month

Climate seasons →																	
January			**February**			**March**			**April**			**May**			**June**		
WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak
H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24

→ Climate seasons																	
July			**August**			**September**			**October**			**November**			**December**		
WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak
H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24

WD: Typical Weekday (Mo-Fr) Peak: Typical Day with Monthly Peak Demand
WE: Typical Weekend (Sa-Su) H1-24: Time step of one hour (24 time steps/day)

Thus, uncertainty models, power flow simulations and microgrid operation calculations, for both grid-connected and islanded modes, are executed per each time step of 1 hour (864-time steps along the planning horizon). The resulting information in each time step is used to calculate the objective functions and constraint values as part of the optimization problem. Depending on the geographical region, seasons are considered from the climate historical data per each month of the year.

Number of stages

Considering the strategy formulated before, the POMMP and POMMP2 planning methodologies are formulated as single-stage planning with the possibility to be expanded to stage-by-stage planning. Therefore, in both cases, a single stage of one year is planned at the time and then it can be followed by the next stage.

4. Multi-objective microgrids planning optimization problem formulation

The planning task involves a decision-making process thatin the microgrid's case can be as complex as the number of decision variables, planning objectives and constraints increase. The solution to the planning problem is linked to the definition of an optimization problem, which ultimately is part of the solving strategy. The definition of the optimization problem can be seen as the main task for the formulation and implementation of a microgrid planning methodology. This task comprises the definition of a group of objective functions, decision variables and constraint functions that will use the mathematical models of the microgrid and its components, described in Chapter 3. Furthermore, the optimization problem is solved in three parts: model setup, optimization, and decision-making (Branke *et al.*, 2008). In this regard, the definition of the optimization problem, solving tools, decision-making techniques and performance evaluation strategies are described in this chapter for the POMMP and POMMP2 methodologies. Different possibilities for the definition of the optimization problem were explored and reviewed from existing proposals in the literature. Hence, the mathematical functions for modeling the planning objectives, the structure for the decision variables vector and mathematical equations for modeling different intentional and unintentional constraints in the planning process are described in Section 4.1. Furthermore, modeling, optimization and assessment tools, as well as multi-criteria decision-making technique are presented in Sections 4.2 and 4.3, respectively, while optimization performance indicators are described in Section 4.4.

The optimization problem definition and optimization algorithms here described are based on the published research by Contreras *et al.* (2018), Contreras *et al.* (2019) Rodriguez *et al.* (2020) and Contreras *et al.* (2020b). For the description of the objective functions, decision variables and constraint functions consider the subscripts summarized in Table **4-1**

4.1. Optimization problem definition

For the POMMP and POMMP2 methodologies, the microgrid planning problem is defined as a constrained true-multi-objective optimization problem with three objective functions, $\mathrm{N_d}$ decision variables, $\mathrm{N_{ic}}$ inequality constraint functions and $\mathrm{N_{ec}}$ equality constrain functions, as it is described below in equation (4-1).

Table 4-1.: Main subscripts in the optimization problem definition

Subscripts	Description
mt, wt, pv	Microturbines, wind turbines, photovoltaics
ba	Battery units
c	Generation technologies with continuous sizing variables: PV
g	Generation technologies with discrete sizing variables: WT and MT
j	Set of technologies ($g \cup c$)
b	Set of storage technologies
i	Set of technologies ($j \cup b$)
l, bus, br	load, Bus or branch (lines)
clu/mg	Cluster = MG
λ	Loop (cycle) in the network
m, d, h	Month 1, 2, ..., 12, day type weekday, weekend, peak day, hour 1, 2, ..., 24
$t(m, d, h)$	Time step along the horizon planning
λ	Loop (cycle) in the network
d	Decision variable (in the optimization problem)
ic	Inequality constraint
ec	Equality constraint

Minimize

$$\left\{f_1\left(\vec{\mathrm{x}}\right), f_2\left(\vec{\mathrm{x}}\right), f_3\left(\vec{\mathrm{x}}\right)\right\} \tag{4-1}$$

Subject to

$$\begin{aligned} \mathrm{x}_{d_{min}} \leq \mathrm{x}_d \leq \mathrm{x}_{d_{max}} \quad & d = 1, 2, \ldots, \mathrm{N_d} \\ g_{ic}\left(\vec{\mathrm{x}}\right) \leq 0 \quad & ic = 1, 2, \ldots, \mathrm{N_{ic}} \\ h_{ec}\left(\vec{\mathrm{x}}\right) = 0 \quad & ec = 1, 2, \ldots, \mathrm{N_{ec}} \end{aligned}$$

The optimization problem involves three conflicting objective functions that we want to minimize simultaneously and constitutes an objective vector $\vec{\mathrm{z}} = f\left(\vec{\mathrm{x}}\right) = \left[f_1\left(\vec{\mathrm{x}}\right), f_2\left(\vec{\mathrm{x}}\right), f_3\left(\vec{\mathrm{x}}\right)\right]^T$ that belong to a three-dimensions *objective space* $\vec{\mathrm{z}} \in \mathbb{R}^3$. A possible solution to the planning problem is a decision variables vector of $n = \mathrm{N_d}$ decision variables: $\vec{\mathrm{x}} = (\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \ldots, \mathrm{x}_n)^{\mathrm{T}}$ that constitutes the *decision variables space* $\vec{\mathrm{x}} \in \mathbb{R}^n$. Thus, for each solution $\vec{\mathrm{x}}$ in the decision variables space, there is a point $\vec{\mathrm{z}}$ in the objective space, since objective vectors are images of decision variables vectors. Furthermore, the solutions $\vec{\mathrm{x}}$ that satisfy the constraint functions and variables limits form a *feasible decision variable space* $\mathrm{S} \subset \mathbb{R}^n$, and the image of the feasible region in the objective space is the *feasible objective space* $\mathrm{Z} \subset \mathbb{R}^3$ (Branke *et al.*, 2008). We will refer to the objective vectors as particles or individuals and to the decision variables vector as solutions.

The goal of the true-multi-objective is to find the set of alternatives (optimal objective vectors) with different trade-offs and satisfying all constraints, called Pareto optimal solutions, or non-dominated solutions. None of the solutions in the Pareto optimal solutions set is a better solution than the other since the objective vector is considered optimal if none of their components can be improved without degenerating at least one of the other components.

It is important to highlight that is hardly found another proposal in literature for solving the microgrid planning problem with a true-multi-objective optimization formulation with more than two objective functions. In POMMP and POMMP2, the proposal of including the third objective was inspired in the wide range of potential contradictory planning objectives that have been identified in the literature and can be required depending on the case study (See Chapter 1). Therefore, two objective functions are defined under the thesis of maximizing the potential microgrid services provision capacity and minimizing the investments and operating costs at the same time that the profit cost is maximized. While the remaining third objective is defined to offer certain flexibility for planning goals preferences. For example, this objective function was formulated as a performance objective in both POMMP and POMMP2, as it is described below. Nonetheless, this can also be adapted to different technical, environmental, or social goals depending on the study case and stakeholders' priorities or requirements.

A formulation with more than three objective functions is also feasible. However, in practice, more than three objectives also lead to difficulties for a visualization of the results and final decision-making. Therefore, we consider that three objectives offer a convenient balance between planning flexibility and optimization complexity.

4.1.1. Modification of the multi-objective formulation for the topology planning with POMMP2

Additionally to the formulation of the multi-objective optimization problem, we re-define the optimization problem to include the topology planning as it is described below. The optimization problem in POMMP2 was formulated as a bi-level optimization, where the high-level optimization comprises the true-multi-objective optimization formulated in equation (4-1) and the lower-level optimization involves the optimal partitioning of the network in clusters for the further topology planning[1]. Therefore, objective functions are calculated in two levels (equation (4-2)) based on the graph theory modeling of the microgrid network described in Chapter 3.

[1]We use the concept of bi-level optimization. However, the optimization is concretely managed with the metaheuristic optimization technique at the upper level considering the optimal graph portioning and topology formation in the lower-level. This strategy may be called a **quasi-bi-level** optimization. However, it is an optimization concept that it is hardly found in literature until now, and would required specific research.

Minimize

$$f\left(\vec{\mathrm{x}}\right)=\begin{cases}\left[f_{\mathrm{k1}}\left(\vec{\mathrm{x}}\right),f_{\mathrm{k2}}\left(\vec{\mathrm{x}}\right),f_{\mathrm{k3}}\left(\vec{\mathrm{x}}\right)\right]^{\mathrm{T}} & \text{if} \quad |\mathrm{V(G)}|<\mathrm{k}\\ \left[f_{1}\left(\vec{\mathrm{x}}\right)f_{2}\left(\vec{\mathrm{x}}\right),f_{3}\left(\vec{\mathrm{x}}\right)\right]^{\mathrm{T}} & \text{if} \quad |\mathrm{V(G)}|=\mathrm{k}\end{cases} \tag{4-2}$$

Subject to

$$\begin{array}{ll}\mathrm{x}_{d_{min}}\leq\mathrm{x}_{d}\leq\mathrm{x}_{d_{max}} & d=1,2,\ldots,\mathrm{N_d}\\ g_{ic}\left(\vec{\mathrm{x}}\right)\leq 0 & ic=1,2,\ldots,\mathrm{N_{ic}}\\ h_{ec}\left(\vec{\mathrm{x}}\right)=0 & ec=1,2,\ldots,\mathrm{N_{ec}}\end{array}$$

Where f_{k1}, f_{k2}, f_{k3} represent the penalization of the objective functions for the condition, $\mathrm{G}=(\mathrm{V},\mathrm{E})$ is the undirected graph that represent the distribution network with a fixed number of vertices ($|\mathrm{V}|=\mathrm{N}_{bus}$) and a number of edges ($|\mathrm{E}|=|\vec{\mathrm{x}}_{br}|\ \forall\ \mathrm{x}\neq 0$), $\mathrm{k}=\mathrm{N}_{bus}$ is a minimum number of vertices that should be connected and $|\mathrm{V(G)}|$ is the number of connected vertices for the graph G. Equation (4-2) means that the objective functions will be calculated depending on the resulting connected or disconnected graph from the decision variables set for the branch selection $\vec{\mathrm{x}}_{br}$. In this way, for a disconnected graph G, the objective functions will be calculated as in equation (4-3).

$$f_{\mathrm{k1}}\left(\vec{\mathrm{x}}\right)=f_{\mathrm{k2}}\left(\vec{\mathrm{x}}\right)=f_{\mathrm{k3}}\left(\vec{\mathrm{x}}\right)=M\times\left(\mathrm{k}-|\mathrm{V(G)}|\right) \tag{4-3}$$

Where M is an arbitrary penalty value to guarantee that $f_{\mathrm{k1}}>>f_1$, $f_{\mathrm{k2}}>>f_2$ and $f_{\mathrm{k3}}>>f_3$ (two orders of magnitude for this research).
It can be noticed that the strategy here proposed uses the metaheuristic optimization algorithm for solving a single set of objective vectors with two different calculations. One for a not desired disconnected topology and one for the fully connected network.
Therefore, the objective functions and decision variables are calculated as follows for a fully connected network, which is shared with the calculations of the POMMP methodology.

4.1.2. Objective functions for POMMP and POMMP2

The set of objective functions defined for POMMP and POMMP2 are mathematically described below.

Maximization of the residual power for the AS provision

The fully available residual active power to be exported to the main grid is calculated in equation (4-4) for both POMMP and POMMP2 methodologies (Contreras *et al.*, 2019, 2020b).

$$f_1(\vec{x}) = -\frac{1}{N_t}\left[\sum_{t=1}^{N_t}\left(\sum_j P_{DG_{j,t}}(\vec{x}) \pm \sum_b P_{DS_{b,t}}(\vec{x}) - \right.\right.$$
$$\left.\left. - \sum_l P_{load_{l,t}}(\vec{x}) - P_{loss_t}(\vec{x})\right)\right], \text{ [MW]} \quad \forall \quad t \quad (4\text{-}4)$$

The function has a negative value since it is desirable to maximize the residual capacity of the microgrid. j represents the set of DG technologies, b the set of storage technologies, and l the set of loads, t is a time step of n_t time steps.

Minimization of the investment, maintenance and operating cost

The economic function in equation (4-5) is the second objective function for the POMMP and POMMP2 methodologies, and considers the operating and investment costs of a microgrid in a typical year (Contreras *et al.*, 2019, 2020b).
The main considerations are:

- Customer's loads are modeled accordingly to the planning horizon.
- Investment costs are annualized based on an interest rate and the lifetime of the technology.
- The installed capacity of PV and BA technologies are sized using continuous decision variables while the capacity of the MT and WT technologies are sized trough discrete decision variables following the proposal of Cardoso *et al.* (2017) as will be described in detail in the following sections.
- MT technologies can be extended to other dispatchable technologies such as internal combustion engines (ICE), gas turbines, and even fuel cells.

The objective function in equation (4-5) includes a set of desired components of costs to be optimally minimized in the microgrid in a year, including the regulated tariff for public services, the energy purchasing cost, the operating and maintenance costs (O&M) for the on-site generation, the annualized capital costs of the DERs, and the revenues from sales of electricity and the provision of AS to the grid.
Furthermore, the objective function has been updated to include the capital costs for the installation of distribution lines per distance unit to optimize the microgrid topology planning in POMMP2, part (g).

$$
\begin{aligned}
f_2(\vec{\mathrm{x}}) = [& \\
& \sum_{m} \mathrm{T}_{\mathrm{F}_m} && \rightarrow \text{(a)} \\
& + \sum_{m}\sum_{d}\sum_{h} \mathrm{U}_{\mathrm{L}_{m,d,h}} \cdot \mathrm{T}_{\mathrm{E}_{m,d,h}} && \rightarrow \text{(b)} \\
& + \sum_{j}\sum_{m}\sum_{d}\sum_{h} (\mathrm{G}_{\mathrm{T}_{j,m,d,h}}) \cdot (\mathrm{C}_{\mathrm{VC}_{j,m}} + \mathrm{C}_{\mathrm{OMV}_j}) && \rightarrow \text{(c)} \\
& + \sum_{g} \mathrm{I}_{\mathrm{G}_g} \cdot \max(\mathrm{P}_g) \cdot (\mathrm{C}_{\mathrm{CCD}_g} \cdot \mathrm{An}_g + \mathrm{C}_{\mathrm{OMF}_g}) && \rightarrow \text{(d)} \\
& + \sum_{c} (\mathrm{C}_{\mathrm{FCC}_c} \cdot \mathrm{Cap}_c) \cdot \mathrm{An}_c + \mathrm{Cap}_c \cdot \mathrm{C}_{\mathrm{OMF}_c} && \rightarrow \text{(e)} \\
& + \sum_{b} (\mathrm{C}_{\mathrm{FCC}_b} \cdot \mathrm{Cap}_b) \cdot \mathrm{An}_b + \mathrm{Cap}_b \cdot \mathrm{C}_{\mathrm{OMF}_b} && \rightarrow \text{(f)} \\
& + \sum_{br} \mathrm{L}_{br} \cdot (\mathrm{C}_{\mathrm{CCB}_{br}} \cdot \mathrm{An}_{br}) && \rightarrow \text{(g)} \\
& - \sum_{m}\sum_{d}\sum_{h} \mathrm{G}_{\mathrm{S}_{m,d,h}} \cdot \mathrm{T}_{\mathrm{Ex}_{m,d,h}} \cdot \mathrm{b}_{\mathrm{TEx}_{m,d,h}} && \rightarrow \text{(h)} \\
& - \sum_{m}\sum_{d}\sum_{h} \mathrm{G}_{\mathrm{S}_{m,d,h}} \cdot \mathrm{S}_{\mathrm{MCP}_{m,d,h}} \cdot \mathrm{b}_{\mathrm{S}_{m,d,h}} && \rightarrow \text{(i)} \\
& - \sum_{m}\sum_{d}\sum_{h} \mathrm{G}_{\mathrm{S}_{m,d,h}} \cdot \mathrm{NS}_{\mathrm{MCP}_{m,d,h}} \cdot \mathrm{b}_{\mathrm{NS}_{m,d,h}} && \rightarrow \text{(j)} \\
& - \sum_{m}\sum_{d}\sum_{h} \mathrm{G}_{\mathrm{S}_{m,d,h}} \cdot \mathrm{R}_{\mathrm{UpMCP}_{m,d,h}} \cdot \mathrm{b}_{\mathrm{RUp}_{m,d,h}} && \rightarrow \text{(k)} \\
& - \sum_{m}\sum_{d}\sum_{h} \mathrm{G}_{\mathrm{S}_{m,d,h}} \cdot \mathrm{R}_{\mathrm{DnMCP}_{m,d,h}} \cdot \mathrm{b}_{\mathrm{RDn}_{m,d,h}} && \rightarrow \text{(l)} \\
& \quad]\,, \ [\$\mathrm{MUSD}] \qquad \forall \quad m, d, h
\end{aligned}
\tag{4-5}
$$

The generation costs are considered from part (a) to (g) in equation (4-5). Part (a) accounts for the fixed operation cost for electricity in month m, where $\mathrm{T}_{\mathrm{F}_m}$ in [\$] is the regulated tariff fixed charge for electricity. Part (b) models the electricity purchased from the power utility, where $\mathrm{U}_{\mathrm{L}_{m,d,h}}$ in [kW] is the electricity purchase at time m, d, h, and $\mathrm{T}_{\mathrm{E}_{m,d,h}}$ in [\$/kWh] is the regulated tariff for electricity. Part (c) relates the variable operation and maintenance costs of generation, where $\mathrm{G}_{\mathrm{T}_{j,m,d,h}}$ in [kW] is the total power generated by the DGs technologies j, $\mathrm{C}_{\mathrm{VC}_{j,m}}$ in [\$/kWh] is the generation cost of DGs technologies j during month m, and $\mathrm{C}_{\mathrm{OMV}_j}$ in [\$/kWh] is the variable annual operation and maintenance costs of the DGs technologies j. Afterwards, parts (d), (e) and (f) model the fixed annual operation and maintenance costs for MT, WT, PV and BA, respectively. In these, $\mathrm{I}_{\mathrm{G}_g}$ is the number of units of generation technology g (WT and MT) installed, P_g in [kW] is the active power generated by the WT or MT technology g, $\mathrm{C}_{\mathrm{CCD}_g}$ in [\$/kW] is the turnkey capital cost of MT or WT generation technology g , $\mathrm{An}_{c,g,k}$ are the annuity factor for investments in technologies c, g or k, $\mathrm{C}_{\mathrm{OMF}_{c,g,k}}$ are the fixed annual operation and maintenance costs of technology c, g or k in [\$/kW], $\mathrm{C}_{\mathrm{FCC}_{c,k}}$ are the fixed capital cost of generation technology c or k in [\$/kW], and $\mathrm{Cap}_{(c,k)}$ in [kW] are the rated power capacity of generation technology c or k.

In equation (4-5), the part (g) has been included **only** for the POMMP2 methodology to consider the investment cost due to the installation of lines per unit of distance (in this case km), which are annualized based on an interest rate and the lifetime of the connections.

Furthermore, the generation revenues are considered from part (h) to (l). Part (h) is the revenue due to the exported power, where $\mathrm{G}_{\mathrm{S}_{m,d,h}}$ in [kW] is the power generated to be exported at time m, d, h, $\mathrm{T}_{\mathrm{Ex}_{m,d,h}}$ in [\$/kWh] is the regulated tariff for electricity export at time m, d, h, and $\mathrm{b}_{\mathrm{TEx}_{m,d,h}}$ is the binary decision of selling electricity to the stock at time m, d, h. Parts (i), (j), (k) and (l) are the revenues due to AS supplying for spinning reserve, non-spinning reserve, and frequency up- and down-regulation, respectively. In these parts, $\mathrm{S}_{\mathrm{MCP}_{m,d,h}}$, $\mathrm{NS}_{\mathrm{MCP}}$, $\mathrm{R}_{\mathrm{UpMCP}}$ and $\mathrm{R}_{\mathrm{DnMCP}}$ are the regulated tariff for the spinning reserve, non-spinning reserve and frequency up- and down-regulation, respectively, while the binary variables were described in Chapter 3.

Minimization of the microgrid annual power losses

The power losses are introduced in the optimization problems as a performance objective function in the POMMP[2] and POMMP2 methodologies. This final formulation is based on the work in (Contreras *et al.*, 2018) and the planning objectives review in (Li *et al.*, 2017; Arefifar and Mohamed, 2014b). The objective function is given in equation (4-7), and the losses are found from results of a probabilistic power flow simulation for each time-step in the methodology.

$$f_3(\vec{\mathrm{x}}) = \frac{1}{\mathrm{N}_t}\left[\sum_{t=1}^{\mathrm{N}_t} \mathrm{P}_{\mathrm{loss}_t}(\vec{\mathrm{x}})\right], \ [\mathrm{MW}] \quad \forall \quad t \tag{4-6}$$

Microgrid active power mismatch in islanded-mode

As it was mentioned, the third objective function is intended to offer a certain level of flexibility from the planning stage. For that reason, the version of the POMMP methodology presented in (Contreras *et al.*, 2019) uses as third objective the microgrid's active power mismatch value in islanded-mode given by equation (4-7).

[2]The POMMP methodology in (Contreras *et al.*, 2019) considers the objective function of power mismatch in islanded-mode.

$$f_3(\vec{\mathrm{x}}) = \frac{1}{\mathrm{N}_t}\left[\sum_{t=1}^{\mathrm{N}_t}\left(\sum_j \mathrm{PI}_{\mathrm{DG}_{j,t}}(\vec{\mathrm{x}}) \pm \sum_b \mathrm{PI}_{\mathrm{DS}_{b,t}}(\vec{\mathrm{x}}) - \right.\right.$$
$$\left.\left. - \sum_l \mathrm{PI}_{\mathrm{lshed}_{l,t}}(\vec{\mathrm{x}}) - \mathrm{PI}_{\mathrm{loss}_t}(\vec{\mathrm{x}})\right)\right], \text{ [MW]} \quad \forall \quad t \quad (4\text{-}7)$$

In this case, the power values PI correspond to the power flow results of the simulations during the islanded mode operation. The main reason of considering the power mismatch in islanded mode is the possibility of consider demand response strategies such as load shedding that in the equation is represented by the $\mathrm{PI}_{\mathrm{lshed}}$, where $\sum_l \mathrm{PI}_{\mathrm{lshed}_{l,t}} < \sum_l \mathrm{PI}_{\mathrm{load}_{l,t}}$.
The results of this strategy can be consulted in (Contreras *et al.*, 2019). However, for this dissertation, the annual power losses were used as third objective function for both POMMP and POMMP2 methodologies. This modification of the third objective function in POMMP aims to facilitate comparisons with the POMMP2 methodology.

4.1.3. Decision variables for POMMP and POMMP2

Decision variables are a fundamental part of the planning strategy and consequently optimization problem definition. For the planning methodologies here proposed, one of the main differences between the POMMP and POMMP2 methodologies can be found in the formulation of the decision variables vector.
In both cases, POMMP and POMMP2, the main planning decision is intended to be made over the optimal size and location of the power resources in the microgrid. However, POMMP2 additionally includes the holistic planning of the microgrid's topology. Therefore, two different sets of decision variables were defined depending on the methodology.

Decision variables for the POMMP methodology

For this methodology, two different sets of decision variables are defined. The first group of variables represents the DERs capacity, and the second set of variables is the location of the DERs in the microgrid. Furthermore, the power capacities are included in the first group as discrete integer or continuous variables depending on the technology. Thus, the capacity of MT and WT are selected based on discrete variables that symbolize specific steps for predefined standard or commercial accessible capacities, while the capacity of PV and BA systems are defined as continuous variables considering the modular characteristic of the systems and small capacities of each unit compared with the whole system size. This approach was adopted from the proposal of Cardoso *et al.* (2017) for the DER-CAM tool. Regarding the DERs location in the second set, the decision variables are defined as discrete variables that describe each node of the microgrid. These decision variables set are defined in equation (4-8). The graphic representation of the decision variables vector is shown in Figure 4-1.

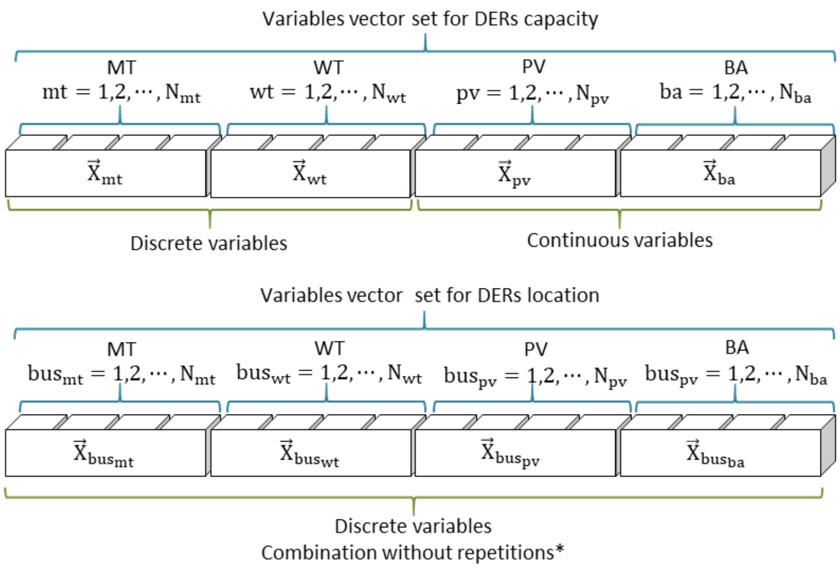

Figure 4-1.: Decision variables model for the POMMP methodology

$$\vec{x} = \left[\vec{x}_{\mathrm{mt}}, \vec{x}_{\mathrm{wt}}, \vec{x}_{\mathrm{pv}}, \vec{x}_{\mathrm{ba}}, \vec{x}_{\mathrm{bus_{mt}}}, \vec{x}_{\mathrm{bus_{wt}}}, \vec{x}_{\mathrm{bus_{pv}}}, \vec{x}_{\mathrm{bus_{ba}}}\right]^T \tag{4-8}$$

Where

$$\begin{aligned}
\vec{x}_{\mathrm{mt}} &= [x_1, x_2, \ldots, x_{mt}]^{\mathrm{T}} & \vec{x}_{\mathrm{bus_{mt}}} &= [x_1, x_2, \ldots, x_{mt}]^{\mathrm{T}} & mt &= 1, 2, \ldots, \mathrm{N_{mt}} \\
\vec{x}_{\mathrm{wt}} &= [x_1, x_2, \ldots, x_{wt}]^{\mathrm{T}} & \vec{x}_{\mathrm{bus_{wt}}} &= [x_1, x_2, \ldots, x_{wt}]^{\mathrm{T}} & wt &= 1, 2, \ldots, \mathrm{N_{wt}} \\
\vec{x}_{\mathrm{pv}} &= [x_1, x_2, \ldots, x_{pv}]^{\mathrm{T}} & \vec{x}_{\mathrm{bus_{pv}}} &= [x_1, x_2, \ldots, x_{pv}]^{\mathrm{T}} & pv &= 1, 2, \ldots, \mathrm{N_{pv}} \\
\vec{x}_{\mathrm{ba}} &= [x_1, x_2, \ldots, x_{ba}]^{\mathrm{T}} & \vec{x}_{\mathrm{bus_{ba}}} &= [x_1, x_2, \ldots, x_{ba}]^{\mathrm{T}} & ba &= 1, 2, \ldots, \mathrm{N_{ba}}
\end{aligned}$$

Where $\mathrm{N_{bt}}$, $\mathrm{N_{wt}}$, $\mathrm{N_{pv}}$ and $\mathrm{N_{ba}}$ are the number of BT, WT, PV and BA possible units or systems, respectively. Thereore, the total number of decision variables $\mathrm{N_d} = 2 \times (\mathrm{N_{mt}} + \mathrm{N_{wt}} + \mathrm{N_{pv}} + \mathrm{N_{ba}})$.
It is established for the POMMP and POMMP2 methodologies that only one DER unit/system can be placed per bus. Therefore, the initialization of the vector set for the location of DERs is modeled as discrete variables with a repair strategy to ensure a combination without repetitions ($*$ in Figure 4-1).

Decision variables for the POMMP2 methodology

For the POMMP2 methodology, the decision variables are organized in the vector $\vec{x}$. The vector has been modified to include a set of binary variables that represent the connected

(1) or disconnected (0) state of a line in a set of possible connections. The decision variables vector model for the holistic planning perspective is described in equation (4-9) for N_{br} possible branches selection in the topology planning. The modification to the decision variable vector for the POMMP2 methodology is shown in Figure **4-2**.

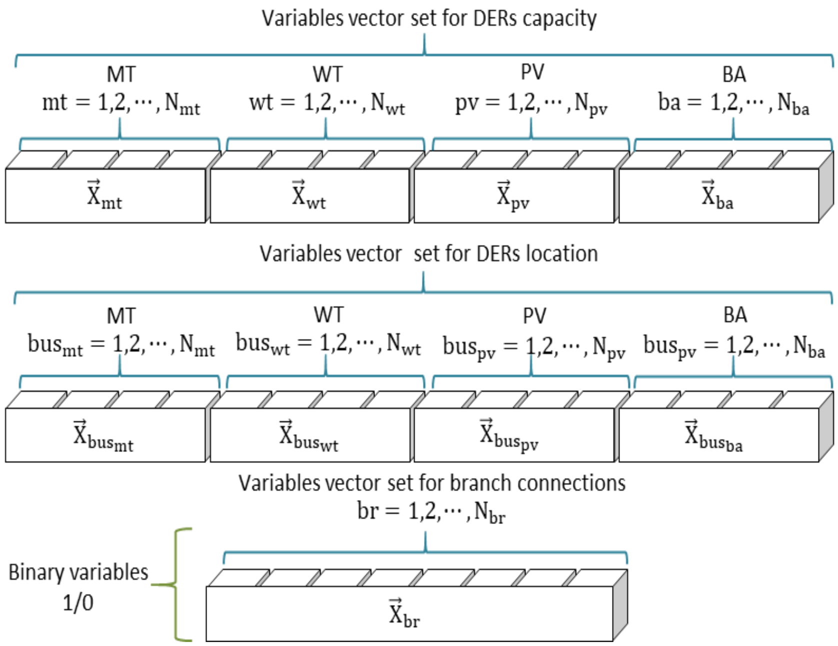

Figure 4-2.: Decision variables model for an holistic POMMP2 planning perspective, adapted from Contreras *et al.* (2020b)

$$\vec{x} = \left[\vec{x}_{mt}, \vec{x}_{wt}, \vec{x}_{pv}, \vec{x}_{ba}, \vec{x}_{bus_{mt}}, \vec{x}_{bus_{wt}}, \vec{x}_{bus_{pv}}, \vec{x}_{bus_{ba}}, \boldsymbol{\vec{x}_{br}}\right]^{T} \tag{4-9}$$

Where

$$\begin{aligned}
&\vec{x}_{mt} = [x_1, x_2, \ldots, x_{mt}]^{T} && \vec{x}_{bus_{mt}} = [x_1, x_2, \ldots, x_{mt}]^{T} && mt = 1, 2, \ldots, N_{mt}\\
&\vec{x}_{wt} = [x_1, x_2, \ldots, x_{wt}]^{T} && \vec{x}_{bus_{wt}} = [x_1, x_2, \ldots, x_{wt}]^{T} && wt = 1, 2, \ldots, N_{wt}\\
&\vec{x}_{pv} = [x_1, x_2, \ldots, x_{pv}]^{T} && \vec{x}_{bus_{pv}} = [x_1, x_2, \ldots, x_{pv}]^{T} && pv = 1, 2, \ldots, N_{pv}\\
&\vec{x}_{ba} = [x_1, x_2, \ldots, x_{ba}]^{T} && \vec{x}_{bus_{ba}} = [x_1, x_2, \ldots, x_{ba}]^{T} && ba = 1, 2, \ldots, N_{ba}\\
& && \boldsymbol{\vec{x}_{br} = [x_1, x_2, \ldots, x_{br}]^{T}} && \boldsymbol{br = 1, 2, \ldots, N_{br}}
\end{aligned}$$

In this case, the number of decision variables are $N_d = 2 \times (N_{mt} + N_{wt} + N_{pv} + N_{ba}) + \mathbf{N_{br}}$.

4.1.4. Constraint functions for POMMP and POMMP2

The microgrid planning problem can comprise several types of constraints (Cardoso *et al.*, 2017; Gazijahani and Salehi, 2017; Arefifar and Mohamed, 2014b; Zidan *et al.*, 2013). In the POMMP and POMMP2 methodologies, different constraints are adapted from Cardoso *et al.* (2017).

Energy balance and buses voltage limits in the Microgrid

The energy balance includes the generated, exported, imported, consumed power and losses in islanded and grid-connected modes in equations (4-10)-(4-11), where $\mathrm{T_{oPG}}_{m,d,h}$, $\mathrm{P_{Aexp}}_{m,d,h}$, $\mathrm{P_{Aimp}}_{m,d,h}$, $\mathrm{T_{oPD}}_{m,d,h}$, and $\mathrm{P_{loss}}_{m,d,h}$ are the total generated, exported, imported, demanded, and lost active power in [kW] for the Microgrid in grid-connected mode (equation (4-10)) and islanded mode (symbols with "I" in equation (4-11)), respectively. Additionally, the voltage V limits at each node are constrained in equation (4-12).

$$\mathrm{T_{oPG}}_{m,d,h} - \mathrm{P_{Aexp}}_{m,d,h} + \mathrm{P_{Aimp}}_{m,d,h} = \mathrm{T_{oPD}}_{m,d,h} + \mathrm{P_{loss}}_{m,d,h} \quad \forall\, m,d,h \quad [\mathrm{kW}] \tag{4-10}$$

$$\mathrm{T_{oPGI}}_{m,d,h} = \mathrm{T_{oPDI}}_{m,d,h} + \mathrm{P_{lossI}}_{m,d,h} \quad \forall\, m,d,h \quad [\mathrm{kW}] \tag{4-11}$$

$$\mathrm{V_{min}} \leq \mathrm{V}_{bus,m,d,h} \leq \mathrm{V_{max}} \quad \forall\, bus,m,d,h \quad [\mathrm{V}] \tag{4-12}$$

Operation limits of distributed generators

The maximum and minimum operating limits of each DG, the maximum number of operation hours and the available physical area for distributed energy resources installation are considered in equations (4-13)-(4-15).

$$\sum_g \mathrm{Min\ P}_g \leq \mathrm{G_T}_{g,m,d,h} \leq \sum_g \mathrm{Max\ P}_g \quad \forall\, m,d,h \quad [\mathrm{kW}] \tag{4-13}$$

$$\sum_m \sum_d \sum_h \mathrm{G_T}_{g,m,d,h} \leq \sum_g \mathrm{Max\ P}_g \cdot \mathrm{Max\ H}_g \quad \forall\, lm,d,h \quad [\mathrm{kW}] \tag{4-14}$$

$$\mathrm{AU}_{bus,j} \leq \mathrm{ADisp}_{bus,j} \quad \forall\, bus,j \quad (\mathrm{m}^2) \tag{4-15}$$

where H_g is the number of hours that the units with technology g (MT or WT) can operate, $\mathrm{G_T}$ is the total power generated by technology g in [kW], $\mathrm{AU}_{bus,j}$ is the used physical area at the bus by a DG technology j [m^2], and ADisp_{bus} is the available physical area at the bus [m^2]. Notice that the other variables are part of (4-5).

Operation limits of storage systems

As with the generation, the operating limits of storage systems are constrained. Limits such as energy balance, maximum and minimum power flow capacity in a given node, and the verification of the scheduled dispatch for the supply of AS are taken into account in equations (4-16)-(4-25).

$$\begin{aligned}\mathrm{S}_{\mathrm{Out}_{b,m,d,h}} &= \mathrm{S}_{\mathrm{OutMR}_{b,m,d,h}} + \mathrm{S}_{\mathrm{OutRUp}_{b,m,d,h}} + \\ &+ \mathrm{S}_{\mathrm{OutS}_{b,m,d,h}} + \mathrm{S}_{\mathrm{OutNS}_{b,m,d,h}} \quad \forall\, b,m,d,h \quad [\mathrm{kWh}]\end{aligned} \tag{4-16}$$

$$\mathrm{S}_{\mathrm{In}_{b,m,d,h}} = \mathrm{S}_{\mathrm{InMR}_{b,m,d,h}} + \mathrm{S}_{\mathrm{InRDn}_{b,m,d,h}}\ \forall\ \ b,m,d,h\ [\mathrm{kWh}] \tag{4-17}$$

$$\begin{aligned}\mathrm{SOC}_{b,m,d,h} \cdot \mathrm{C}_{\mathrm{ba}_b} &= \mathrm{S}_{\mathrm{In}_{b,m,d,h}} - \mathrm{S}_{\mathrm{Out}_{b,m,d,h}} \\ &+ \mathrm{SOC}_{b,m,d,h-1} \cdot \mathrm{C}_{\mathrm{ba}_b}(1-\eta_{\mathrm{ba}_b}) \quad \forall\, b,m,d,h \quad [\mathrm{kWh}]\end{aligned} \tag{4-18}$$

$$\mathrm{SOC}_{b,m,d,1} = \mathrm{SOC}_{b,m,d,24} \quad \forall\, b,m,d \quad [\%] \tag{4-19}$$

$$\mathrm{SOC}_{b,m,d,h} \geq \mathrm{MDOD}_b \quad \forall\, b,m,d,h \quad [\%] \tag{4-20}$$

$$\mathrm{SOC}_{b,m,d,h} \leq 1 \quad \forall\, b,m,d,h \quad [\mathrm{kWh}] \tag{4-21}$$

$$\mathrm{S}_{\mathrm{In}_{b,m,d,h}} \leq \mathrm{C}_{\mathrm{ba}_b} \quad \forall\, b,m,d,h \quad [\mathrm{kWh}] \tag{4-22}$$

$$\mathrm{S}_{\mathrm{Out}_{b,m,d,h}} \leq \mathrm{C}_{\mathrm{ba}_b} \quad \forall\, b,m,d,h \quad [\mathrm{kWh}] \tag{4-23}$$

$$\mathrm{S}_{\mathrm{In}_{b,m,d,h}} \leq \mathrm{b}_{\mathrm{ch}_{b,m,d,h}} \cdot \mathrm{M} \quad \forall\, b,m,d,h \quad [\mathrm{kWh}] \tag{4-24}$$

$$\mathrm{S}_{\mathrm{Out}_{b,m,d,h}} \leq \mathrm{b}_{\mathrm{dch}_{b,m,d,h}} \cdot \mathrm{M} \quad \forall\, b,m,d,h \quad [\mathrm{kWh}] \tag{4-25}$$

Where $\mathrm{S}_{\mathrm{In}_{b,m,d,h}}$ and $\mathrm{S}_{\mathrm{Out}_{b,m,d,h}}$, for the battery b , are the input and output power during one hour in [kWh]; $\mathrm{S}_{\mathrm{InMR}_{b,m,d,h}}$ $\mathrm{S}_{\mathrm{OutMR}_{b,m,d,h}}$ are the input and output during one hour in [kWh] of battery b for the internal excess or consumption of the Microgrid, and $\mathrm{S}_{\mathrm{OutS}_{b,m,d,h}}$, $\mathrm{S}_{\mathrm{OutNS}_{b,m,d,h}}$, and $\mathrm{S}_{\mathrm{OutRUp}_{b,m,d,h}}$ are the b battery's output power for the spinning, non-spinning, and frequency up-regulation in [kWh], respectively. Furthermore, η_{ba_b} are the losses due to self-discharge in battery b, and M is an arbitrary large number for binary considerations. Other variables in equations (4-16)-(4-25) where described in the model of the battery in Chapter 3.

Export and import of energy to the microgrid

It is guaranteed that there is no incoming and outgoing energy flow from and to the main grid at the same time in equations (4-26)-(4-27).

$$\mathrm{U}_{\mathrm{L}_{m,d,h}} \leq \mathrm{b}_{\mathrm{ps}_{m,d,h}} \cdot \mathrm{M} \quad \forall\, m,d,h \quad [\mathrm{kW}] \tag{4-26}$$

$$\mathrm{G}_{\mathrm{S}_{m,d,h}} \leq (1-\mathrm{b}_{\mathrm{ps}_{m,d,h}}) \cdot \mathrm{M} \quad \forall\, m,d,h \quad [\mathrm{kW}] \tag{4-27}$$

Where $\mathrm{b}_{\mathrm{ps}_{m,d,h}}$ is the binary decision of selling or purchasing electricity to the main grid, $\mathrm{U}_{\mathrm{L}_{m,d,h}}$ is the electricity purchase, and $\mathrm{G}_{\mathrm{S}_{m,d,h}}$ is the enerated power to be exported.

Ancillary services

The dispatch of AS is constrained in the microgrid by the scheduled dispatch, supplying time window, power capacity, and a minimum bid to participate in each of the energy markets in equations(4-28)-(4-39). First, the binary decisions for the AS supplying are verified along with the horizon planning with equations (4-28) to (4-31).

$$\mathrm{S}_{m,d,h} \leq \mathrm{b}_{\mathrm{S}_{m,d,h}} \cdot \mathrm{M} \quad [\mathrm{kW}] \tag{4-28}$$

$$\mathrm{NS}_{m,d,h} \leq \mathrm{b}_{\mathrm{NS}_{m,d,h}} \cdot \mathrm{M} \quad [\mathrm{kW}] \tag{4-29}$$

$$\mathrm{R}_{\mathrm{Up}_{m,d,h}} \leq \mathrm{b}_{\mathrm{RUp}_{m,d,h}} \cdot \mathrm{M} \quad [\mathrm{kW}] \tag{4-30}$$

$$\mathrm{R}_{\mathrm{Dn}_{m,d,h}} \leq \mathrm{b}_{\mathrm{RDn}_{m,d,h}} \cdot \mathrm{M} \quad [\mathrm{kW}] \tag{4-31}$$

Where $\mathrm{S}_{m,d,h}$, $\mathrm{NS}_{m,d,h}$, $\mathrm{R}_{\mathrm{Up}_{m,d,h}}$, and $\mathrm{R}_{\mathrm{Dn}_{m,d,h}}$ are the total active power, in [kW], generated for spinning reserve, non-spinning reserve, and up- and down-frequency regulation, respectively. Furthermore, $\mathrm{b}_{\mathrm{S}_{m,d,h}}$, $\mathrm{b}_{\mathrm{NS}_{m,d,h}}$, $\mathrm{b}_{\mathrm{RUp}_{m,d,h}}$, and $\mathrm{b}_{\mathrm{RDn}_{m,d,h}}$ are the binary decision of selling certain type of AS.
The AS supplying time is constrained for each type from (4-32) to (4-35). For this purpose, θ represents the AS supplying time [h].

$$\sum_{h'} b_{S_{m,d,h}} \geq (b_{S_{m,d,h}} - b_{S_{m,d,h-1}}) \cdot \theta \quad : h' = \{h, h+1, .., h+\theta\} \tag{4-32}$$

$$\sum_{h'} b_{NS_{m,d,h}} \geq (b_{NS_{m,d,h}} - b_{NS_{m,d,h-1}}) \cdot \theta \quad : h' = \{h, h+1, .., h+\theta\} \tag{4-33}$$

$$\sum_{h'} b_{RUp_{m,d,h}} \geq (b_{RUp_{m,d,h}} - b_{RUp_{m,d,h-1}}) \cdot \theta \quad : h' = \{h, h+1, .., h+\theta\} \tag{4-34}$$

$$\sum_{h'} b_{RDn_{m,d,h}} \geq (b_{RDn_{m,d,h}} - b_{RDn_{m,d,h-1}}) \cdot \theta \quad : h' = \{h, h+1, .., h+\theta\} \tag{4-35}$$

The constrains (4-36) to (4-39) are intended to guarantee a minimum capacity in the microgrid to assure its participation in the AS markets. $\mathrm{S}_{\mathrm{MinBid}}$, $\mathrm{NS}_{\mathrm{MinBid}}$, $\mathrm{R}_{\mathrm{UpMinBid}}$, and $\mathrm{R}_{\mathrm{DnMinBid}}$ are the minimum bid for spinning and non-spinning reserve market, and frequency up- and down-regulation markets.

$$\mathrm{S}_{m,d,h} \geq \mathrm{b}_{\mathrm{S}_{m,d,h}} \cdot \mathrm{S}_{\mathrm{MinBid}} \quad [\mathrm{kW}] \tag{4-36}$$

$$\mathrm{NS}_{m,d,h} \geq \mathrm{b}_{\mathrm{NS}_{m,d,h}} \cdot \mathrm{NS}_{\mathrm{MinBid}} \quad [\mathrm{kW}] \tag{4-37}$$

$$\mathrm{R}_{\mathrm{Up}_{m,d,h}} \geq \mathrm{b}_{\mathrm{RUp}_{m,d,h}} \cdot \mathrm{R}_{\mathrm{UpMinBid}} \quad [\mathrm{kW}] \tag{4-38}$$

$$\mathrm{R}_{\mathrm{Dn}_{m,d,h}} \geq \mathrm{b}_{\mathrm{RDn}_{m,d,h}} \cdot \mathrm{R}_{\mathrm{DnMinBid}} \quad [\mathrm{kW}] \tag{4-39}$$

Topology formation - POMMP2

The proposal of a holistic perspective for the planning of microgrids considering simultaneously DERs size and location with topology formation in POMMP2 is one of the main contributions of the research presented in this dissertation. For that purpose, the planning methodology considers a cluster-based topology in a networked microgrid with a flexible decision making to form full radial-based, loop-based, mesh-based, or mixed topologies. Therefore, the set of constraint functions is enhanced to consider topology-planning restrictions based on the graph models described in Chapter 3. Four constraint functions were included in POMMP2 to constrain the optimal formation of clusters and the topology. Accordingly, the constraint (4-40) guarantees that all the buses of the distribution network are connected by at least one branch.

$$\left|\mathrm{V}(\mathrm{G}_{\mathrm{i}_p})\right| = \mathrm{k}_p \qquad \forall\, p \tag{4-40}$$

Where V are the vertices (buses) of the networked microgrid, G_i is the initial networked microgrid graph, p represent the current individual of the population and $\mathrm{k}_p = \mathrm{N}_{bus}$ is a subset of vertices $\mathrm{k} \in \mathrm{V}$ that represent the minimum number of vertices that should be connected.

Constraint (4-41) guarantees a number of clusters n_{clu} in the complete networked microgrid equal to a pre-defined number N_{clu}. Furthermore, the methodology can configure a full radial-based ($\mathrm{N}_{\lambda_{mg}} = 0$), loop-based ($\mathrm{N}_{\lambda_{mg}} = 1$), mesh-based ($\mathrm{N}_{mg} > 1$) or mixed topologies. In this respect, the number of loops per each cluster $\mathrm{n}_{\lambda_{mg}}$ is constrained to $\mathrm{N}_{\lambda_{mg}}$ in equation

(4-42). POMMP2 is proposed to have a cluster per each dispatchable DG ($\mathrm{N}_{clu} = \mathrm{N}_{mt}$), and a loop per each cluster microgrid ($\mathrm{N}_{\lambda_{mg}} = 1$).

$$\mathrm{n}_{clu,p} = \mathrm{N}_{clu,p} \qquad \forall\, p \tag{4-41}$$

$$\mathrm{n}_{\lambda_{mg,p}} = \mathrm{N}_{\lambda_{mg,p}} \qquad \forall\, mg, p \tag{4-42}$$

The number of buses (vertices) $|\mathrm{k}_\lambda|$ that belong to a loop Λ ($\mathrm{k}_\lambda \in \mathrm{V}_\lambda$) is constrained in equation (4-43) to a minimum number of buses $\min|\mathrm{k}_\lambda| = 5$ to avoid undesirable small loops.

$$|\mathrm{k}_{mp,\lambda,p}| \geq \min|\mathrm{k}_\lambda| \qquad \forall\, mg, \lambda, p \tag{4-43}$$

Loops in graph theory are known as cycles and there are several algorithms available in the literature that can be used to find the fundamental cycles in the clusters and networked microgrid. Λ is the typical symbol in graph theory for representing a loop (cycle) in the network and this must not be confused by the weight vector $\boldsymbol{\lambda}$ of the Tchebycheff decomposition method of the MOEA/D optimization algorithm in Section 4.4.

4.2. Metaheuristic true-multi-objective optimization algorithms for the solution of the optimization problem

To solve this multi-objective optimization problem it is necessary to choose a suitable optimization algorithm. In this case, it was decided from existing results in state of the art to model the optimization problem based on a population-based metaheuristic optimization technique, and more specifically, evolutionary algorithm, Figure **4-3**.

A well-known true-multi-objective version for the Genetic algorithms called "Non-dominated Sorting Genetic Algorithm - NSGAII" and a powerful algorithm for the solution of true-multi-objective approaches with more than two objective functions called "Multi-objective Evolutionary Algorithm Based on Decomposition - MOEA/D" were chosen as potential algorithms for solving the optimization problem in the POMMP and POMMP2 methodologies. The selection of the optimization algorithms was a result of the analysis of different existing techniques through the reviews and research of Rodriguez *et al.* (2020), Lopez Rivera and Rodríguez Bejarano (2019), Acosta *et al.* (2018), Acosta León (2017) and Florez Quiroga and Parrado Herrera (2017). Then, for example, bio-inspired optimization algorithms such as Multi-objective Cukooo' Search (Acosta *et al.*, 2018) and Bacterial Foraging Multi-objective Algorithm - BCMOA (Florez Quiroga and Parrado Herrera, 2017) were evaluated in these grade projects to this doctoral thesis.

It is important to highlight that the POMMP and POMMP2 methodologies can be relatively easily adapted to be solved with different population-based metaheuristic. It is not possible

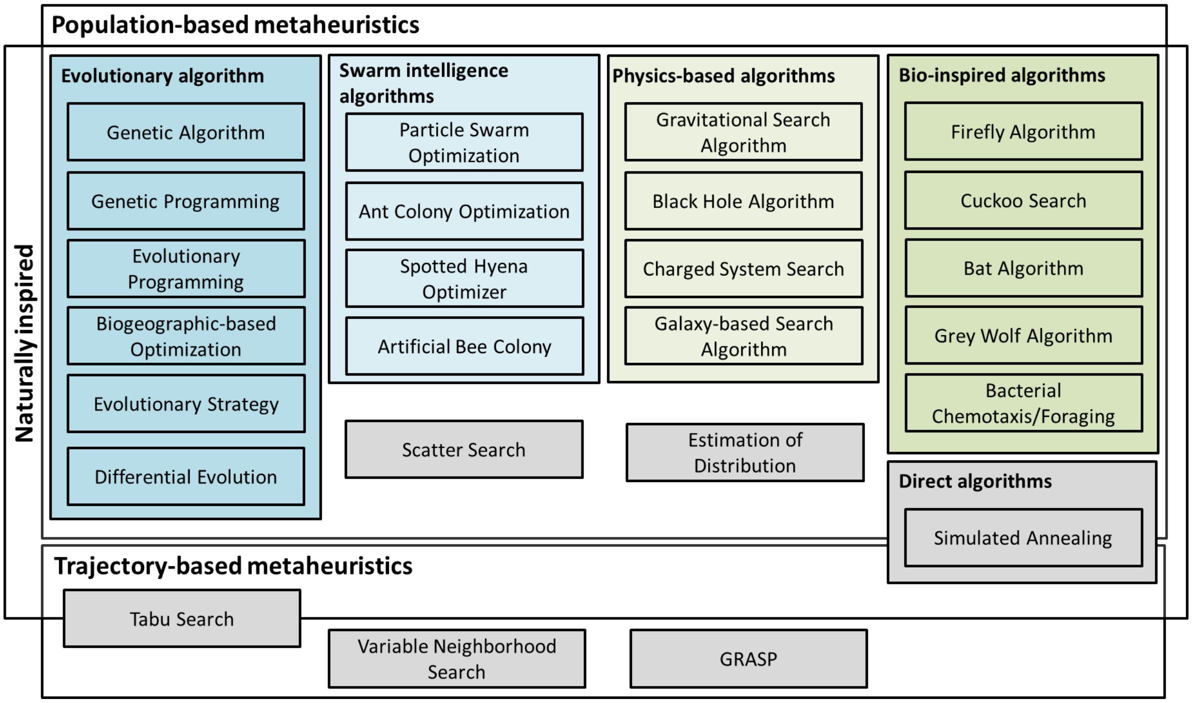

Figure 4-3.: Overview of existing metaheuristic optimization techniques

to select an unique algorithm with absolute suitability for the solution of this particular optimization problem. Therefore the evaluation of optimization algorithms for solving the microgrid planning problem is still a research area.
A detailed explanation of the NSGAII and MOEA/D algorithms is left out of the scope of this dissertation. However, the main features of both algorithms are summarized below with the aim to facilitate the understanding of the methodologies by readers.

4.2.1. Non-dominated Sorting Genetic Algorithm- NSGA-II

The NSGAII algorithm was proposed for the first time by Deb *et al.* (2002a). The metaheuristic method is an evolutionary multi-objective optimization algorithm based on a fast elitist non-sorting technique to find a set of Pareto optimal solutions.
The procedure starts with the generation of an initial population of size $\mathrm{N_{pop}}$, where each individual of the population has a decision variables vector with $\mathrm{N_d}$ decision variables that will be an image in the objectives space of each possible solution $\vec{\mathrm{X}}(\mathrm{N_{pop}} \times \mathrm{N_d})$. For the POMMP and POMMP2 methodologies, three important adaptations are managed for the algorithm:

- The decision variables are generated based on a continuous or discrete nature, reason why the algorithm has is to handle discrete variables. In that way, the continuous selection is rounded to the nearest integer value, and the process is done before the objective functions (fitness functions) calculation and evaluation (Contreras *et al.*, 2019).

- The random initialization technique is adopted. The initial first part of the decision variables vectors (DG units size) is selected randomly, while the algorithm is modified to consider a random sampling of combinations without repetition for choosing among all the buses the initial second part of the decision variables vector (DG units location).

- Binary variables for the POMMP2 methodology are handled as discrete variables with lower and upper limits between 0 and 1.

After the initial population has been generated, individuals are evaluated for each of the objective functions and are classified based on the **non-dominance principle**[3]. With this, a set of so-called weak-Pareto fronts are formed with a number of solutions, which are assigned a *fitness value* equal to the ranking they occupy. Then, using the binary tournament selection operator, the parents are selected, and applying the cross and mutation operators, a population of $\mathrm{N_{pop}}$ children is obtained. Now, for the next generations the main cycle can be summarized in three parts:

- **Part 1:** A population of size $2\mathrm{N_{pop}}$ is formed with the combination of the population of parents and children. This is done to ensure the so-called elitism, where the previous and current population are included for the analysis in each generation. This population is organized according to the non-dominance criteria, and its individuals are grouped in different weak-Pareto fronts depending on the number of dominated solutions. A *fitness value* is assigned to the individuals belonging to each of these Weak-Pareto fronts.

- **Part 2:** A new population with original size $\mathrm{N_{pop}}$ is formed. For completing the size, it starts with the first weak-Pareto front with the best value of *fitness*. Depending on the size of this first front, individuals of the subsequent fronts are used to complete the population size. For that purpose, the subsequent fronts are organized in descending order according to a so-called crowded-comparison operator (operator proposed to stimulate a diversity of the solutions), and the best solutions are selected to complete the original population's number of individuals.

- **Part 3:** In the new population, the parents are chosen through binary tournament selection operator. Afterward, a population of children is generated through the combination and mutation operators. However, although the binary tournament selection operator is used, the selection criteria are now based on the crowded-comparison operator [4].

[3]The non-dominance principle can be consulted in (Branke *et al.*, 2008, Chapter 3).

[4]The crowded-comparison operator can be consulted in (Deb *et al.*, 2002a)

The use of an elitist-based fast non-dominated sorting approach and a method for preserving diversity in the solutions based on the parameter-less crowded-comparison operator are two of the main characteristics of the proposal in NSGAII (Deb *et al.*, 2002a).

The microgrid planning is a constrained-optimization problem. Therefore, the proposed constrained-domination principle for handling the constrained optimization problem is used (Deb *et al.*, 2002a). The method is based on binary tournament selection, where two solutions are chosen from the population and the best solution is chosen. With the presence of constraints, each solution must be feasible or not feasible. Thus, there can be three situations: 1) Both solutions are feasible; 2) One is feasible and the other is not; and 3) Both are not feasible. Hence, with the constrained domination principle, any feasible solution has a better nondomination rank than any infeasible solution, since feasible solutions are ranked according to their non-domination level based on the objective function values, and among two not feasible solutions, the solution with a smaller constraint violation has a better rank (Deb *et al.*, 2002a).

For the POMMP and POMMP2 methodologies, the NSGAII code for Matlab in (Song, 2020) is adopted. Therefore, binary tournament selection, intermediate (arithmetic) crossover and Gaussian (normal) mutation operators are used. Furthermore, the maximum number of generations (iterations) is chosen as stop criteria.

Consequently, Population size, number of generations, intermediate crossover ratio, and scale and shrink value for the Gaussian mutation are tuning parameters for the optimization algorithm in the planning methodologies. The scale parameter determines the standard deviation of the random number generated in the Gaussian mutation, while the shrink parameter modifies the mutation range as the optimization progress goes forward.

4.2.2. Multiobjective Evolutionary Algorithm Based on Decomposition - MOEA/D

The selection of the MOEA/D was based on the study of the state of the art of the grade project of Lopez Rivera and Rodríguez Bejarano (2019).

The MOEA/D algorithm was proposed by Zhang and Li (2007) to solve the multi-objective optimization problem through the decomposition of the problem into N scalar optimization sub-problems. For that purpose, so-called scalarization functions are used to decompose the original optimization into sub-problems that are simultaneously solved to formed generations with the best solutions found for each sub-problem. Therefore, the optimal solutions of the neighborhood sub-problems should be similar, and the relations among these sub-problems in a neighborhood are defined based on the distances between their aggregation coefficient vectors. Hence, each sub-problem is optimized by using information only from its neighboring sub-problems depending on the decomposition method. To obtain a discrete representation of the whole Pareto set, the group of single-optimization problems to be solved should maintain the following properties:

- The solution to one of the sub-problems must provide an element of the Pareto front of the original multi-objective problem.
- Every element of the Pareto optimal front should be available as a solution of the single-objective optimization of a sub-problem.

There are several strategies to convert the set of Pareto solutions of the multi-objective optimization problem into a number of scalar optimization problems. However, based on our research in (Rodriguez *et al.*, 2020), the Tchebycheff decomposition approach is used for the POMMP and POMMP2 methodologies.

Tchebycheff Approach

Tchebycheff method is used to decompose the Pareto front of the multi-objective problem into $\mathrm{N_{pop}}$ scalar optimization sub-problems that are minimized simultaneously (Zhou *et al.*, 2012). Therefore, in this approach, the objective function of the jth scalar optimization problem is given by (4-44).

$$\text{minimize} \quad g^{\text{th}}(\vec{\mathrm{x}}|\boldsymbol{\lambda}^j, \vec{\mathrm{z}}^*) := \max_{1\leq i\leq m} \left\{\lambda_i^j|\mathrm{f}_i(\vec{\mathrm{x}}) - \mathrm{z}_i^*|\right\} \tag{4-44}$$

Where

- $m = 3$ is the number of objective functions in the original multi-objective optimization problem.
- $\vec{\mathrm{x}} \in \mathrm{S}$ is the decision variables vector of the original multi-objective optimization problem ($f(\vec{\mathrm{x}}) : S \to \mathbb{R}^m$).
- $\boldsymbol{\lambda}^j = \vec{\lambda}^j = [\lambda_1^j, \lambda_2^j, \ldots, \lambda_m^j]^{\mathrm{T}}$ is a coefficient weight vector in the jth objective function g^{th} in the way that $\lambda_i \geq 0$ for all $i = 1, 2, \ldots, m$ and $\sum_{i=1}^{m=3} \lambda_i = 1$.
- $\boldsymbol{\lambda}^1, \ldots, \boldsymbol{\lambda}^{\mathrm{N}}$ is an even spread weight vector set, where N is equivalent to the population $\mathrm{N_{pop}}$.
- $\vec{\mathrm{z}}^* = [\mathrm{z}_1^*, \mathrm{z}_2^*, \ldots, \mathrm{z}_m^*]^{\mathrm{T}}$ is the reference point vector. For example, $\mathrm{z}_i^* = \min f_i(\vec{\mathrm{x}}|\vec{\mathrm{x}} \in \mathrm{S})$ for all $i = 1, 2, \ldots, m$.

Hence, MOEA/D minimizes simultaneously all these N sub-problems' objective functions in each single iteration. For each sub-problem j, the optimal solution to equation (4-44) ($g^{\text{th}}(\vec{\mathrm{x}}|\boldsymbol{\lambda}^j)$ is a Pareto optimal point of the original multi-objective optimization problem in equations (4-1). Therefore, for each Pareto optimal point $\vec{\mathrm{x}}^*$ exist a weight vector in the jth sub-problem $\boldsymbol{\lambda}^j$ such that $\vec{\mathrm{x}}^*$ is the optimal solution of g^{th}, and each optimal solution of g^{th} is a Pareto optimal solution of the original multi-objective optimization problem (Zhang and Li, 2007). Therefore, it is possible to find different Pareto optimal solutions by altering the weight vector $\boldsymbol{\lambda}^1, \ldots, \boldsymbol{\lambda}^{\mathrm{N}}$.

MOEA/D general procedure

MOEA/D defines sets of weight vectors called neighborhoods. Each neighborhood is composed of the closest weight vectors (regarding euclidean distance) concerning each other. In any iteration, the performance of each individual in the MOEA/D is evaluated with respect to the other individuals belonging to the same neighborhood until the optimal individual is selected (Zhang and Li, 2007). From the MOEA/D point of view, an individual is a solution for a sub-problem.
MOEA/D uses genetic operators to preserve the characteristics of the individuals with the best performance and maintain the diversity of the population (Rodriguez *et al.*, 2020). A reproductive plan that includes crossover and Gaussian mutation operators has been used for the POMMP methodology.
The input parameters for the algorithm are: the original multi-objective optimization problem, a stopping criteria, in this case, the number of iterations, the number of sub-problems (e.g. $\mathrm{N} = \mathrm{N_{pop}}$)), and a parameter T that represents the neighborhood size. Afterward, the main steps of the MOEA/D can be shortly summarized as follow[5].

- **Step 1 - Initialization:** For the initialization, a uniform spread N weight vectors are created. Afterward, all possible neighborhoods are formed based on the Euclidean distance between any two weight vectors and the defined neighborhood size T. Furthermore, a random initial population of $\vec{\mathrm{x}}^1, \ldots, \vec{\mathrm{x}}^{\mathrm{N}}$ is generated. In this case, as well as with NSGAII, a rounding strategy and repair technique is implemented for considering discrete variables, and variables with combinations without repetition for the DERs location. Finally, an initial reference point vector $\vec{\mathrm{z}}^T$ is also found for the objective function f_i This point represents the best value found so far for the function f_i.

- **Step 2 - Update:** For each sub-problem, two individuals in the neighborhood are selected and genetic operators are used to generating a new solution. The set of new solutions is improved by a heuristic repair technique, in this case, the variables limits and constraint violations are evaluated to generate a repaired solution that falls inside the feasible decision variable space S. Afterward, the reference value vector $\vec{\mathrm{z}}^T$ is updated, as well as all the neighborhood solutions and the so-called *external population -EP* thatis used to store non-dominated solutions found during the search.

- **Step 3 - Stopping criteria:** If stopping criteria is satisfied, then stop and output EP. Otherwise, Step 2 is repeated.

In MOEA/D, as well as other genetic algorithms, the quality of the approach depends on the set of parameters of the optimization algorithm. In this case, the parameters are used for the construction of the sub-problems' optimization objective and the genetic operators.

[5]A detailed explanation of the procedure can be consulted in (Zhang and Li, 2007).

Thus, population size, number of generations, neighborhood size T, scale parameter for the standard deviation of the Gaussian mutation, F to control the amount of genetic material transmitted by parents and CR for setting the probability of applying the crossover operator to an individual in the population are parameter for the MOEA/D tuning.

4.3. Multi-criteria decision making for final planning solution

Planning and decision making are processes that interact in the present to ultimately select the "best" or most preferred solution from a set of current alternatives that would lead to fulfilling future requirements or goals (Branke *et al.*, 2008; Seifi and Sepasian, 2011). As we have mentioned before, this type of decision making is categorized as an optimization problem (because we would like to choose the optimal alternative) (Seifi and Sepasian, 2011), and for problems with multiple conflicting objectives (or criteria), the decision-making problem is known as Multi-Criteria Decision Making (MCDM) (Branke *et al.*, 2008).

We have also mentioned that decision making in true-multi-objective optimization is accomplished *a posteriori* once the set of alternatives (solutions in the Pareto optimal set) are known. For that purpose, decision-makers should establish preferences and articulate the final selection of a single solution from the set of alternatives.

The MCDM process is not a trivial task that must be addressed carefully. Therefore, the POMMP and POMMP2 include a decision making stage as part of the methodologies. In this context, the MCDM technique known as Analytic Hierarchy Process (AHP) was chosen for that purpose.

The AHP is selected based on the research in the grade project of Ortiz Hernández and Santafé Sanabria (2018). They review different MCDM such as the Technique for Order of Preference by Similarity to Ideal Solution - TOPSIS or the Multi-attribute Utility Theory - MAUT. However, the AHP technique was the one that offered more advantages. The same advantages are identified by the review in (Kumar *et al.*, 2017) They highlight the benefits of the AHP for the energy planning problem.

4.3.1. The Analytic Hierarchy Process - AHP, a multi-criteria decision-making technique

The AHP technique was proposed by Saaty (1990). In the AHP, pairs of criteria and possible solutions are compared based on a predefined relevance-level scale (De Brito and Evers, 2016). The problem is hierarchically discomposed and ranked, making the decision in a descendant order. The strategy was formulated by Ortiz Hernández and Santafé Sanabria (2018) as a combination from Ayadi *et al.* (2017), Alonso and Lamata (2006) and Saaty (2008). The approaches were re-formulated for the POMMP and POMMP2 methodologies as follow.

1) The decision-making is organized as a hierarchic structure with three levels, Figure **4-4**. The main goal is on the Level 1. In Level 2, the decision-making criteria are set as each one of the three objective functions. In Level 3, the alternatives that will be evaluated are established. For this purpose, each criterion has p alternatives, which are each a solution in the Pareto set for each objective function, and are the output of the NSGA-II.

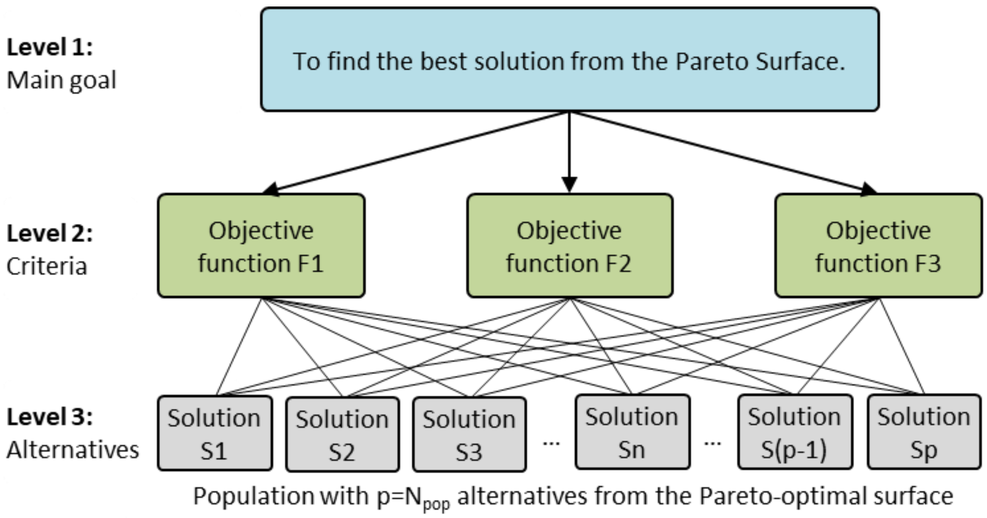

Figure 4-4.: Hierarchic structure used for the decision-making, adapted from Contreras *et al.* (2019)

2) The Objective functions (Level 2) are weighted by comparing in pairs based on the decision-maker criteria and the question, "how relevant is the objective function with respect to the other?". For answering this question, the Saaty's scale with 9 relevance levels is used (Saaty, 2008), Table **4-2**. This comparison gives rise to the comparison matrix B for n = 3 objective functions (criteria) (4-45).

$$\mathrm{B} = \begin{bmatrix} 1 & \mathrm{b}_{12} & \cdots & \mathrm{b}_{1\mathrm{n}} \\ \mathrm{b}_{21} & 1 & \cdots & \mathrm{b}_{2\mathrm{n}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{b}_{\mathrm{n}1} & \mathrm{b}_{\mathrm{n}2} & \cdots & 1 \end{bmatrix} \tag{4-45}$$

Where b_{ij} and $\mathrm{b}_{ji} = 1/\mathrm{b}_{ij}$ are the weight for each pair of objective functions based on Saaty's scale and $\mathrm{b}_{ij} = 1/\mathrm{b}_{ji}$.

3) The consistency among the weights is reviewed with the maximum eigenvalue of B and the consistency index. In this way, the maximum eigenvalue ($\lambda_{\max}$) of the matrix B is calculated in equation (4-46).

Table 4-2.: The fundamental scale of absolute numbers, Saaty (2008)

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
2	Weak or slight	Intermediate value
3	Moderate importance	Experience and judgement slightly favour one activity over another
4	Moderate plus	Intermediate value
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	Intermediate value
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very, very strong	Intermediate value
9	Extreme Importance	The evidence favouring one activity over another is of the highest possible order of affirmation
Reciprocals of above	If activity i has one of the above non-zero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	A reasonable assumption
1.1 - 1.9	If the activities are petty close	May be difficult to assign the best value but when compared with other contrasting activities the size of the small numbers would not be too noticeable, yet they can still indicate the relative importance of the activities

$$\det(\mathrm{B} - \lambda \mathrm{B}) = 0 \tag{4-46}$$

Afterward, the consistency index is calculated in equation (4-47) accordingly to the proposal in (Saaty, 2008; Alonso and Lamata, 2006).

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n} - 1} \tag{4-47}$$

Where n = 3 is the number of elements to compare (objective functions). The consistency ratio is calculated based on equation (4-48).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathbb{RI}} \tag{4-48}$$

Where $\mathbb{RI}$ is an index formulated by Saaty (2008). A value of CR < 10% is considered acceptable, otherwise the previous step must be reviewed. The values accordingly the comparison matrix is given in Table **4-3**.

Table 4-3.: Consistency ratio index (Saaty, 2008)

n	1	2	3	4	5	6	7	8	9	10
$\mathbb{RI}$	0	0	0,52	0,89	1,11	1,25	1,35	1,40	1,45	1,49

The values in Table **4-3** are given for a matrix of maximum n=10. For bigger matrixes, for this, the equation proposed by Alonso and Lamata (2006) is used, equation (4-49).

$$\lambda_{\mathrm{max}} \leq \mathrm{n} + \alpha(1,7699 \times \mathrm{n} - 4.3513) \tag{4-49}$$

Equation (4-49) depends on two factors: the maximum eigenvalue (λ_{max}) and the required consistency level α. This equation is used for the comparison matrix of the alternatives (solutions), since the number is always higher than 10.

4) The normalized relative relevance for each objective function are calculated based on the geometric mean (4-50):

$$\mathrm{W}_i = \frac{\left(\prod_{i=1}^{\mathrm{n}} \mathrm{b}_{ij}\right)^{1/n}}{\sum_{i=1}^{\mathrm{n}} \left(\prod_{i=1}^{\mathrm{n}} \mathrm{b}_{ij}\right)^{1/\mathrm{n}}} \tag{4-50}$$

Then, the normalized weights give rise to the vector $\vec{\mathrm{W}}_{\mathrm{F}}$, with n = 3 in this case (4-51):

$$\vec{\mathrm{W}}_{\mathrm{F}} = \begin{bmatrix} \mathrm{W}_1 & \mathrm{W}_2 & \cdots & \mathrm{W}_{\mathrm{n}} \end{bmatrix}^{\mathrm{T}} \tag{4-51}$$

5) The alternatives in Level 3 (solutions for each objective function) are weighted as in step 2 following the Saaty's scale of 9 degrees. Thus, the solutions are organized in ascendant or descendant order depending on the maximization or minimization goal, and the Saaty's scale is assigned in this order. This gives rise to the comparison matrix $\mathrm{S}_{(\mathrm{p}\times\mathrm{p})}$ for p = number of solutions = $\mathrm{N}_{\mathrm{pop}}$. Afterward, steps 3 and 4 are applied for S, which lead to a vector $\vec{\mathrm{W}}_{\mathrm{S}}$ for each objective function (4-52).

$$\vec{\mathrm{W}}_{\mathrm{S}} = \begin{bmatrix} \mathrm{W}_{\mathrm{S1}} & \mathrm{W}_{\mathrm{S2}} & \cdots & \mathrm{W}_{\mathrm{Sp}} \end{bmatrix}^{\mathrm{T}} \tag{4-52}$$

6) The ranking of each solution p of the Pareto solutions is calculated with (4-53):

$$\vec{\mathrm{R}}_p = \begin{array}{c} \begin{array}{ccc} \mathrm{F1} & \mathrm{F2} & \mathrm{F3} \end{array} \\ \begin{bmatrix} \mathrm{W_{S1}} & \mathrm{W_{S1}} & \mathrm{W_{S1}} \\ \mathrm{W_{S2}} & \mathrm{W_{S2}} & \mathrm{W_{S2}} \\ \vdots & \vdots & \vdots \\ \mathrm{W_{Sp}} & \mathrm{W_{Sp}} & \mathrm{W_{Sp}} \end{bmatrix} \end{array} \begin{bmatrix} \mathrm{W_{F1}} \\ \mathrm{W_{F2}} \\ \mathrm{W_{F3}} \end{bmatrix} \tag{4-53}$$

7) Finally, the solution in the column vector $\vec{\mathrm{R}}_p$ with the highest ranking is chosen from the optimal Pareto-set of solutions.

4.4. Optimization algorithms performance indicators

In the previous chapters some of the main characteristics regarding the use of metaheuristics and more specifically, population-based evolutionary optimization techniques have been discussed. Moreover, it has been mentioned that metaheuristics provide approximated good solutions to the optimization problem instead of exact solutions. Furthermore, most of the metaheuristic optimization techniques include some form of stochastic optimization, since random operations are used as part of the techniques. Therefore, it has been also depicted the wide range of existing metaheuristic techniques and their common performance's dependence on control parameters. Hence, the performance and appropriateness of the chosen optimization techniques should be evaluated, and parameter tuning activities must be executed to guarantee their performance for the optimization problem.

In that vein, two main performance indicators were used for the evaluation of the NSGAII and MOEA/D algorithms. These are the well-known hypervolume indicator and the so-called coverage indicator. Additionally, repeatability and sensitivity studies are executed, as well as the record of the average required computation machine time.

Hypervolume indicator

The hypervolume is also known as S-metric and measures the volume (case with more than two objective functions) in the objective space that is dominated by a population and bounded by a reference point p (Kramer, 2017; Branke *et al.*, 2008). A higher hypervolume leads to good coverage of the non-dominated solutions to guarantee a better diversity of the approximated Pareto front. Furthermore, with a fixed and dominated reference point (worst point), a higher hypervolume indicates a Pareto front further from the dominated reference point. Currently, there are available existing computation toolboxes or codes for the calculation of the indicator.

Coverage indicator

The coverage metric is also known as C-metric and determines the percentage of solutions that are dominated in a Pareto front from the solutions of another Pareto front. Thus, consider that A and B are two approximations to the Pareto front of a multi-objective optimization problem, the C-metric determines the percentage of solutions in B that are dominated by at least one solution in A. The C-metric can be calculated with equation (4-54) (Zhang and Li, 2007).

$$\mathrm{C}(\mathrm{A},\mathrm{B}) = \frac{|\{u \in \mathrm{B}|\ \exists v\mathrm{A}\ :\ v\ dominates\ u\}|}{|\mathrm{B}|} \tag{4-54}$$

A value $\mathrm{C}(\mathrm{A},\mathrm{B}) = 1$ means that all solutions in B are dominated by someone in A. Contrary $\mathrm{C}(\mathrm{A},\mathrm{B}) = 0$ means that no solution in B is dominated by a solution in A (Zhang and Li, 2007).

5. Probabilistic Multi-objective Microgrid Planning POMMP and POMMP2 methodologies

Up to this point, the required mathematical models, optimization definitions, advanced solving algorithms, assumptions and general complex methods and principles for representing different processes, concepts, and operational behaviors of the microgrid and its components for addressing the planning problem have been described.

The aim of this chapter is to present and analyze a planning methodology, in two versions, that have been proposed to systematically incorporate and employ the elements before mentioned and deliver an optimal solution to the planning problem. The methodologies have been named based on the features of two of the main methods that compose them: **Probabilistic Multi-objective Microgrid Planning (POMMP)** and **Probabilistic Multi-objective Microgrid Planning 2 (POMMP2)** methodologies.

The main purpose of the methodologies is to facilitate the decision making of the size and location of DERs in the microgrid, with the POMMP methodology, and simultaneously with the topology of the microgrid with the POMMP2 methodology. In this fashion, the methodologies comprise three planning objectives for addressing the expansion or transition planning of existing microgrids, ADNs or passive distribution networks under the paradigm of microgrids or networked microgrids with the capacity to provide AS to the main grid. The main features of the methodologies are summarized in Table **5-1**.

In this chapter, Section 5.1 presents and explains the POMMP methodology, while Section 5.2 focuses on the POMMP2 methodology. The POMMP methodology was published by us in (Contreras *et al.*, 2019), and the POMMP2 methodology in (Contreras *et al.*, 2020b). The descriptions in the chapter are based on these two publications.

5.1. The Probabilistic Multi-objective Microgrid Planning methodology (POMMP)

The POMMP methodology is depicted in Figure **5-1** (Contreras *et al.*, 2019). This methodology is based on the selection of a base case (e.g. an existing ADN or passive distribution network). Hence, base case network's configuration data such as topology, line parameters,

Table 5-1.: Main features of the POMMP and POMMP2 methodologies

Feature	POMMP	POMMP2
Probabilistic approach	✓	✓
Location and size of DERs	✓	✓
Topology definition		✓
Networked microgrid based on clusters		✓
Multilevel graph partitioning technique		✓
Heuristic optimization	✓	✓
True-multi-objective optimization (3 objectives)	✓	✓
AS provision capacity	✓	✓
Islanded operation	✓	✓

transformer parameters, and load data must be known and modeled in advance. Furthermore, climate and geographical historical data must be also known, as well as power demand along the planning horizon.
The methodology can be read following the step indexes as follow.

- **Pre-planning stage**

  In the first step of the methodology ①, planning parameters and variables limits are set and loaded. For this step, it should be mentioned that the methodology is sensitive to the generation and storage upper and lower capacity limits. Therefore, it was found from numerical results (see Chapter 6) that the decision variable limits must be defined with an upper value for all the generation capacity variables whose total added rate capacity is higher than the total added peak demand of the base case system. For example, it is known for us (Contreras *et al.*, 2019, 2020b) that a total added rate capacity of the upper limits of the decision variables with a ratio of between three and four times the total added peak demand of the base case system is convenient. The network of the base case is also loaded in this step.

  In the second step ②, three main groups of historical data are arranged and loaded: primary energy (wind speed and solar irradiation), load demand for the planning horizon and market's tariffs. The data must cover a proper number of the historical record.

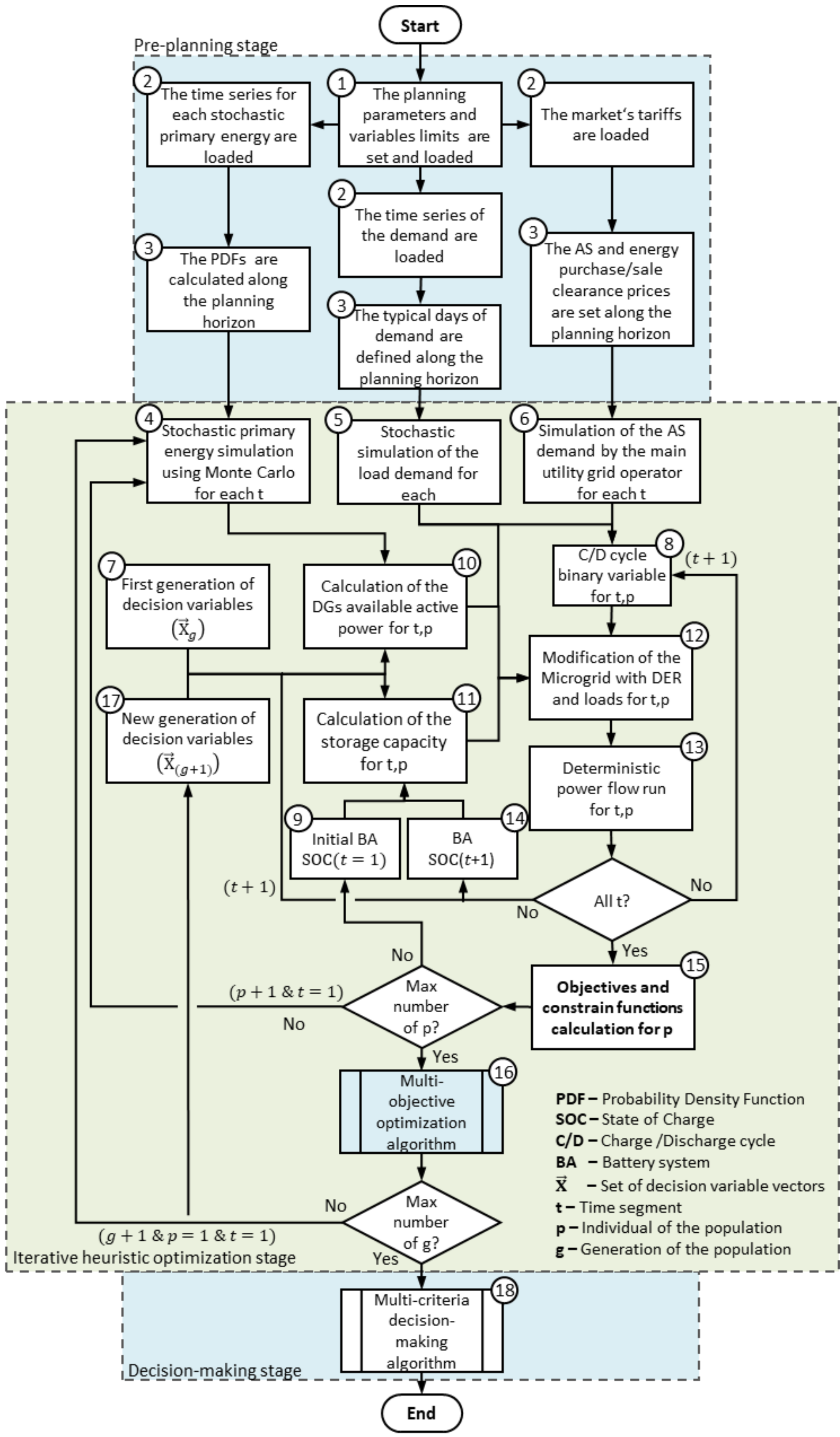

Figure 5-1.: The Probabilistic Multi-objective Microgrid Planning methodology - POMMP, adapted from Contreras *et al.* (2019)

In this research, for example, it has been used time series with a resolution of one hour for 24 hours per day, 365 days per year and three years in the case of the primary energy, which are 26.280 entries per year and 2.190 per month along the planning horizon.

Time series are processed in the third step of the methodology 3. Therefore, PDF for the primary energy and load demand is defined per each time-step (1 hour), of three typical days (weekday, weekend, and peak day) of 24 hours per each month of the planning horizon (See Chapter 3). Furthermore, the AS and energy purchase/sale clearance prices are set for each time step along the planning horizon. The outputs of these steps will be the input data for the subsequent 4-6 steps of the iterative heuristic optimization stage.

- **Iterative heuristic optimization stage**

  The iterative heuristic optimization stage is formulated for a population with a defined size ($\mathrm{N_{pop}}$) and for a maximum number of generations ($\mathrm{N_{gen}}$) as stopping criteria. The iterative methodology starts with the individual generation $g = 1$.

  In step 4, the expected value for the primary energy is found through Monte Carlo Simulation (MCS) for the time step t as was explained in Chapter 3. Similarly, the load demand percentage is calculated for the time step t in 5, and in 6 the maximum clearing price for defining the type of AS or sale decision in each time step t is simulated. These attributes are common for all the population ($\forall\ p \quad p = 1, \ldots, \mathrm{N_{pop}}$) of the generation g.

  In the next step of the methodology 7, the initial decision variables vector $\vec{\mathrm{X}}_g$ for the first generation $g = 1$ is generated. Depending on the type of decision variable, discretization and random combination (without repetition) techniques are used for generating the initial population of decision variables accordingly to the strategies described in Chapter 4.

  Subsequently, the decision binary variable for the supply of AS by shifting between C/D cycles of the battery systems are defined in step 8 for the time step. Furthermore, the SOC of the battery systems are initialized in step 9 for the time step t of the individual in the population p.

  With the information from steps 4, 7 and 9, the available power of the DGs in step 10 and the SOC of the battery systems in step 11 are calculated according to the models described in Chapter 3. These values of the available power and the binary decision variables for the charging/discharging cycles of the BAs (See Chapter 3) are used to modify the microgrid operation in step 12 for the time step t. Afterward, a deterministic power flow for both grid-connected and islanded operation modes is run in step 13. The grid-connected and islanded mode simulation strategy were described in the network model of Chapter 3.

These calculations are iteratively repeated for each time step of 1 hour along the planning horizon, which leads to a total of 864 calculations (1 hour X 24 hours X 3 typical days X 12 months) per each individual p. Between each time step, the SOC of the battery systems is updated in step 14 for $(t+1)$ following the operation model proposed in Chapter 3. Furthermore, a new value of the output power of the DGs and BAs is calculated, as well as the BA cycle is shifted depending on binary variables for the time step $(t+1)$.

Once power flow results have been obtained for all time steps, the objective and constraint functions are calculated for the individual p of the population. These procedure is iteratively repeated until $p = \mathrm{N_{pop}}$. For each individual $(p+1)$, the calculations between steps 4 and 15 are repeated.

When the objective functions and constraint values have been calculated as images of the decision variable vector of each the individual p of the generation g, the multi-objective algorithm chooses the best individuals through the optimization logic of the method in step 16. Afterward, a new decision vector set $\vec{x}_{g+1}$ is generated in step 17. The process from steps 4-15 and 16-17 are iteratively repeated until the maximum number of iterations is reached $g = \mathrm{N_{gen}}$. The optimization algorithm can apply particular strategies as it was described in Chapter 4.

The output of step 16, after all the iterations have been accomplished, is a Pareto optimal set, which is the set of alternatives for the next step 18 of the decision making stage.

- **Decision-making stage**

  The last stage of the methodology is given to the final decision making task. The input to this stage is a Pareto optimal set from the heuristic optimization stage. Thus, in step 18, a single solution is chosen based on the AHP multi-criteria decision-making algorithm explained in Chapter 4. Different preferences depending on the type of stakeholder can be configured in this step of the methodology.

5.2. Planning methodology with a holistic approach to include the microgrid's topology planning - POMMP2

Continuing the main methods and principles proposed in POMMP, the POMMP2 methodology considers not only the size and location of DERs, but also the network topology. In POMMP2, a bi-level optimization strategy is proposed. The methodology enhances the former version by including a novel strategy for a holistic perspective of the planning of networked microgrids maintaining the paradigm of microgrids with AS provision capacity. The mixed generation matrix in POMMP is maintained for POMMP2 with a set of dispatchable DGs (MT, ICE, etc.), non-dispatchable units (PV and WT), and distributed storage (BA). Furthermore, the AS provision is once more based on a fully available extra active power capacity to be exported back to the main grid or to provide spinning/non-spinning operating reserve, and up-/down-frequency regulation. The most remarkable steps of POMMP2 methodology are presented in the methodology as follows in Figure **5-2** (Contreras *et al.*, 2020b).

The methodology is composed of four stages: pre-planning, iterative heuristic optimization, iterative graph partitioning, and decision-making as it is described below.

- **Pre-planning stage:**

  The methodology starts with the pre-planning stage, where all the parameters, limits, PDFs, market characteristics and topology and optimization options are defined and loaded in steps ①-②. Although it is not specifically depicted in the methodology in Figure **5-2**, intermediate steps for the preparation of time series and PDFs of the uncertainty variables and clearing prices are also part of the pre-planning stage such as in POMMP (Figure **5-1**). Hence, data for each time step t of three typical days (weekday, weekend and peak day) are defined per each month along with the planning problem (See POMMP in Section 5.1).

  The output of the pre-planning stage in POMMP2 is the arrangement of data sets for the stochastic generation, load demand and clearing prices of the market. This information is an input to the iterative heuristic optimization stage, where the probabilistic calculations for the primary energy of renewable technologies and load demand are defined with MCS and the maximum clearing prices are determined for defining the microgrid AS bids along the planning horizon.

  The pre-planning stage of POMMP2 is performed the same as in POMMP.

- **Iterative heuristic optimization stage:**

  The second stage (upper-level optimization) is executed by iterative population-based heuristic optimization. The optimization algorithm initializes the decision variables vector $\vec{X}_{p,g}$ in step ③ for all the individuals of the population of the initial generation $g = 1$.

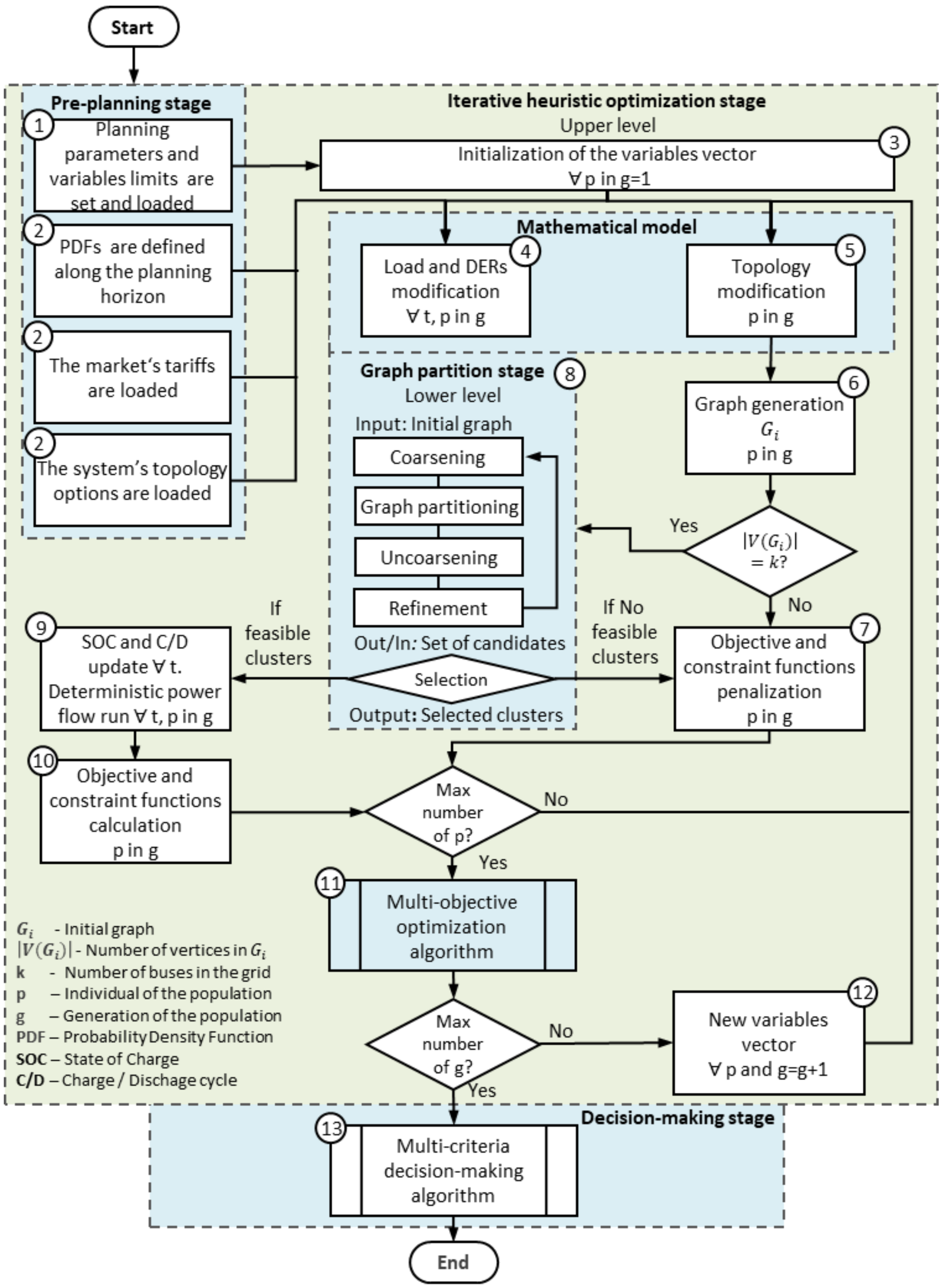

Figure 5-2.: The Probabilistic Multi-objective Microgrid Planning methodology 2 - POMMP2, adapted from Contreras *et al.* (2020b)

Afterward, the mathematical model of the microgrid is modified in step 4 based on the values of the variables and the expected output power of the renewable resources and load demand previously simulated with MCS and the probabilistic model.

One of the main contributions of POMMP2 can be found in step 5, where the networked microgrid is then modeled as a graph $\mathrm{G_i(V, E)}$, where V represent the buses and E the connection lines. In POMMP2, V is always equal to the total number of buses, while the connections E are established by the decision variables as it is described in Chapter 3. The microgrid's topology is modified in this step based on the binary decision variables for the lines connection or disconnection.

The next step 6 is to verify complete graph connectivity since stand-alone buses are forbidden in the methodology. If the networked microgrid is not fully interconnected, objective functions are penalized in step 7 as it is described in Chapter 4 to stimulate convergence and feasibility in the topology and clusters formation.

On the other hand, for the fully connected graph, the **multilevel graph partitioning stage** (Lower-level optimization) is applied in step 8 to find an optimal set of cluster microgrids that constitute the networked microgrid. As it was described in Chapter 3, the adopted graph partitioning is a multilevel iterative approach with coarsening, partitioning, uncoarsening, refinement and selection parts whose output is an optimal clustered networked microgrid. This process is iteratively executed in step 8. The last sub-step in 8 is the selection of a clustered networked microgrid based on the set of candidates.

There can be cases when it is not possible to define a clustered networked microgrid. In this case, in clusters, the objective functions are penalized in step 7 as it is described in Chapter 4. This can happen due to the definition of the decision variables vector (size/location of DERS and topology definition) for the individual p.

On the contrary, if a suitable clustered networked microgrid is defined and selected, the output of the 8 would be a possible topology for a clustered networked microgrid. In this case, the methodology continues with step 9 for the simulation of the microgrid for each time step along with the horizon planning.

For step 9, notice that step 4 indicates a load and DERs modification for each time step as is performed in POMMP. This refers to the iterative simulation of the microgrids per each time step along the planning horizon as in POMMP. Therefore, the topology is defined in the lower level in step 8 and simulations of the clustered networked microgrid are executed for each time step t along the planning horizon. Thus, deterministic power flow is run for four architectures based on the possible operation modes (Refers to Chapter 3): a fully grid-connected networked microgrid with the feeder as slack bus; a complete disconnected networked microgrid with the strongest dispatchable DG as slack bus; and an islanded cluster with their individual dispatchable DG as slack bus.

When the simulations have been run for all the time-steps in step 9, the objective and constraint functions are calculated in step 10 for the individual p. Mathematical models defined in Chapter 3 and the optimization problem (objective and constraint functions) formulated in Chapter 4 are used in steps 9-10 for the calculation of the simulations and calculation objective and constraint values. Here it is important to highlight that POMMP2 offers a flexible configuration of the planning methodology to form full radial-based, loop-based, mesh-based, or mixed topologies. As it was described in Chapter 4, the topology characteristics are evaluated based on constraints of the pre-established aforementioned preferences.

Steps 4-10 are iteratively repeated until ($p = \mathrm{N}_{\mathrm{pop}}$). Each individual p has a decision variable vector $\vec{\mathrm{X}}_{p,g}$. Therefore, the objective vector in 10 is a set of images of each of the possible solutions.

Once $p = \mathrm{N}_{\mathrm{pop}}$, the resulting objective functions and constraints are used by the optimization algorithm in 11 for the optimal exploration and exploitation of the feasible region to find the Pareto optimal solutions. For that purpose, the optimization algorithm generates a more optimal decision variable vector in step 12 for all individuals of the next generation ($g + 1$).

Steps 4-12 are iteratively repeated until the maximum number of generations $g = \mathrm{N}_{\mathrm{gen}}$ is reached. The outcome of the true-multi-objective technique in step 11 is a Pareto optimal set of planning solutions/alternatives with different trade-offs.

- **Decision-making stage**

  The last stage of the methodology is reserved to select a desired solution from the Pareto optimal solutions set. In this way, in step 13, a multi-criteria decision-making strategy based on the AHP technique is used. In AHP, the problem is hierarchically organized, and different pairs of objectives and Pareto solutions are compared at each level to obtain their relative weights and a final ranking of the alternatives regarding decision maker's preferences as it was described in Chapter 4. AHP supports decision-makers to establish priorities and select a single-solution based on the best compromise among solutions.

The outcome of the methodology is a networked microgrid with an optimal selection of the DERs in terms of their capacity and location, as well as the optimal clustering and interconnection of the networked microgrid for the maximization of the residual available power for AS provision, minimization of costs and maximization of profits, and minimization of the annual energy losses in the microgrid.

6. Study cases and results of the probabilistic multi-objective microgrid planning methodology

The POMMP and POMMP2 methodologies are formulated and presented in this dissertation for the planning of MV utility microgrids or networked microgrids with capacity for providing AS to the main grid. The methodologies are proposed as novel tools for comprehensively performing a decision making on the size and location of DERs, in the microgrid with POMMP, and the microgrid's topology, with POMMP2. Nonetheless, the planning of microgrids and other types of local power distribution systems are strongly case-dependent since, unlike traditional systems, local systems such as microgrids involve a large number of DERs with very different operational behavior among them. Therefore, POMMP and POMMP2 are intended to cover main features for the planning under different case-studies and allow adaptations based on, for instance, preferences of stakeholders. For this respect, POMMP and POMMP2 methodologies present key characteristics such as the *a posteriori* decision making competency, the true-multi-objective formulation with three objective functions, the capacity for handling large number and variety of decision variables, the possibility of integrating mixed generation matrix prospect, the formulation of strategies for incorporating renewable and storage resources, the feasibility of considering different type of topologies for microgrids and a framework for enhancing microgrid participation in AS markets.

In this context, this chapter aims to numerically analyze the performance and characteristics of the POMMP and POMMP2 methodologies based on two case studies:

- **Case study 1 - (CS1):** Microgrid planning for the PG&E 69-bus medium voltage distribution network.

- **Case study 2 - (CS2):** Microgrid planning for the IEEE 37-bus medium voltage distribution network.

These two case studies are defined based on known benchmarks and test systems and adapted to cover relevant aspects of the planning methodologies such as market characteristics, base-case structures, topology planning, climate conditions and optimization algorithms.

The test systems are well-known and have been amply used for different studies in the literature. For this research particularly, key reference authors such as Gazijahani and Salehi (2018a) and Arefifar and Mohamed (2014b) base their numerical results on the PG&E 69-bus test system, while authors such as Che *et al.* (2017b) use the IEEE 37 for the topology planning test. In this vein, the results of the research by Contreras *et al.* (2019), Peñaranda *et al.* (2019) and Contreras *et al.* (2018) were presented using the PG&E 69-bus test system, while Contreras *et al.* (2020b) and Cortes, Contreras and Shahidehpour (2018) considered the IEEE 37-bus test system for evaluating the proposed methodologies.
The POMMP and POMMP2 are tested depending on the case study for two different TSO market conditions: California Independent System Operator - CAISO territory, and PJM Interconnection LLC -PJM territory, both in the USA (Zhou *et al.*, 2016). Both markets belong to TSOs, although CAISO is an independent system operator (ISO) and PJM a regional system operator (RSO) in the USA (See Chapter 2). The selection of the markets is based on the results of the grade project of Peñaranda Bayona and Mosquera Duarte (2018) and the DER-CAM data-base information described by Cardoso *et al.* (2017).
The chapter begins in Section 6.1 with a general description of the used planning parameters, market conditions, climate data, load profile data and simulation tools that are common for both case studies. Afterward, the CS1 is used to describe and analyze the parameter tuning process and metaheuristic optimization sensitivity for the solution of the planning problem in Section 6.2. In Section 6.3, the decision-making preferences and AHP strategy for the case studies are defined. The CS1 is particularly studied in Section 6.4, while the CS2 is punctually examined in Section 6.5. Final remarks and analysis of the results are presented in Section 6.6.
The results here described are based on the published research by Cortes, Contreras and Shahidehpour (2018), Contreras *et al.* (2019), Rodriguez *et al.* (2020) and Contreras *et al.* (2020b). However, enhancements are included to improve the understanding and discussion on the performance of the methodologies.

6.1. General description of the planning problem, data sources and solving tools for the case studies

The input data used for the execution of the CS1 and CS2 is described below.

Primary energy time series

For the two case studies, wind and solar historical data have been strategically chosen from the German Meteorological Office (*Deutscher Wetterdienst-DWD*). Time series with a resolution of one hour and a period of three years were used with the option of three possible geographical locations: Dortmund (West-Germany), Kiel (North-Germany), Munich (South-Germany). For this dissertation, the reference time series from the city of Kiel was adopted.

The climate conditions are then characterized by four clear seasons along the planning horizon, which are defined based on the load model explained below for winter, spring, summer and fall. Furthermore, the percentage of cloudy days and average wind power density may be higher than in other places due to the geographical locations close to the European North Sea. However, it is left out of the scope of this dissertation the analysis of the impact of the climate conditions in the planning of microgrids[1]. At the same time, the comparison among the cases presented in this dissertation is considered valid since all of them use the same climate historical data conditions. The renewable primary energy PDFs are presented in Appendix B. The data information can be accessed in the cloud location in (Contreras *et al.*, 2020a).

Load demand time series

The historical data for the load demand is constructed based on the percentage of the peak load accordingly to the IEEE Reliability Test System (Probability Methods Subcommittee, 1979). The load model in (Probability Methods Subcommittee, 1979) offers hourly loads for one year on a per unit basis for reliability studies. The values are organized chronologically so that daily, weekly and seasonal patterns can be modeled. In this regard, the data is divided into weekly peak load in percentage of the annual peak, daily peak load in percentage of the weekly peak and hourly peak load in percentage of the daily peak. The hourly peak load is given by weekday and weekend and suggest a pattern for the winter season between week 1-8 and 44-52, summer season between week 18-30 and spring/fall seasons between week 9-17 and 31-43. This interval of weeks for each season proposed by Probability Methods Subcommittee (1979) represents an application to a winter peaking system. Hence, winter days have a load peak during the evening while summer days have a load peak during afternoons. In this context, for simulations in CS1 and CS2, time series are constructed considering the load model described and a random variation of the weekly, daily and hourly percentage of the peak load in $\pm$ 1%. An overview of the adopted time series for the planning horizon and typical day modeling system is shown in Table **6-1**, while the load profiles are shown in Appendix B.

Market conditions and clearance price for numerical simulations

The economic data used to describe the PJM and CAISO market were obtained in (Stadler, 2008) and (IRENA, 2014). Regarding the Market data, the cities of San Francisco and

[1]The precursory microgrid planning methodology of POMMP proposed in (Contreras *et al.*, 2018) was used by Holguín and Vanegas (2018) for the theoretical planning of a microgrid in the Campus La Paz of the Universidad Nacional de Colombia in the municipality of La Paz, Valledupar Colombia. This case study is left out of the main scope of this dissertation since the final methodologies POMMP and POMMP2 were not used in this study. However, readers can refer to the bachelor research as a reference to other case studies conditions.

Table 6-1.: Overview of the load model for defining the planning horizon and time steps for three typical days in the month

Winter season	Spring season	Summer season

Weakly peak load in percentage of annual peak →

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26

Month 1	Month 2	Month 3	Month 4	Month 5	Month 6

Daily peak load in percentage of weekly peak →

WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak

Hourly peak load in percentage of daily peak →

H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24

Summer season	Fall season	Winter season

→ Weakly peak load in percentage of annual peak

27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52

Month 7	Month 8	Month 9	Month 10	Month 11	Month 12

→ Daily peak load in percentage of weekly peak

WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak	WD	WE	Peak

→ Hourly peak load in percentage of daily peak

H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24	H1-24

WD: Typical Weekday (Mo-Fr) Peak: Typical Day with monthly peak Demand
WE: Typical Weekend (Sa-Su) H1-24: Time step of one hour (24 time steps/day)

Baltimore belonging to the territory of CAISO and PJM, respectively, were selected to implement the planning methodologies in locations with different AS rates and market prices as in (Cardoso *et al.*, 2017). The tariff information used was based on data available in (Stadler, 2008). Furthermore, the Pacific Gas & Electric (PG&E) and Baltimore Gas & Electric (BG&E) generation rates were selected for the cities of San Francisco and Baltimore, respectively, from Cardoso *et al.* (2017), and the transmission rates considered in (Yura, 2014) were added.

The time series of the tariff for exporting energy to the main utility grid (T_{Ex}) were based on the clearing price of the market. The data were obtained for 2014 in (LCG Consulting, 2014) for CAISO market and in (PJM, 2014b) for PJM market. The tariffs for the AS provision were chosen from the 2014 historical time series data of the clearing prices of CAISO and PJM markets (OASIS, 2014; PJM, 2014a). Data for each time step of a typical-day along the planning horizon is calculated as the arithmetic median of the clearing price of the set of values (e.g. weekdays/ weekend of the month). All the market's data used for simulations can be consulted in Appendix B.

Installation area characteristics

POMMP and POMMP2 methodologies admit the constrain of the available installation area for each bus of the base network (See Chapter 4). In this case, an available area is defined for each bus of the test systems in CS1 and CS2 and the values are used in all simulations. The values were aleatory defined with areas between 250m^2 and 1500m^2 for roof areas, and 2500m^2 and 25000m^2 for ground areas[2] as they can be consulted in Appendix B. The average area needed by each PV system was defined as $160\text{W}/\text{m}^2$, while according to Patel (2005, Chapter 5), WTs need a separation of the towers between 2-4 and between 8-12 times the rotor diameter in the parallel and orthogonal axes to the blade rotation, respectively. Accordingly, a minimum separation of 2 and 8 times, and a rotor diameter of 25m were chosen for the WTs technologies used in this research, which lead to a required area of 2500m^2 per WT. Although MT of 30kW or 60kW are commercially build in modular cells with average required areas of 1.5m^2, for the configuration of the systems in this research, MT, ICE, GT and BA technologies are considered to require in average the area equivalent to a 20ft ($2,4\text{m} \times 6\text{m} = 14,6\text{m}^2$) or 40ft ($2,4\text{m} \times 12,2\text{m} = 29,3\text{m}^2$) standard shipping container.

Used computational tools

The components of the POMMP and POMMP2 methodologies are programmed and modeled using MATLAB code language, toolboxes and extensions. More specifically, the optimization algorithm and mathematical models are programed in the MATLAB version 9.4. The base network is modeled in MATPOWER version 7.0, which is also used to run deterministic AC power flow simulations as part of the methodologies.
Power flow simulations are run conventionally based on the MATPOWER models and Newton-Raphson method solver.
Additionally, the Statistic and Machine Learning Toolbox version 11.3 is used to incorporate functions for the analysis and calculations based on PDFs as part of the uncertainties probabilistic model.

6.2. Parameter tuning and performance analysis for the optimization problem solution

Parameter tuning can be a complex task and even constitute an optimization problem for the proper selection of an optimal combination of parameters (Eiben and Smit, 2011). In the parameter tuning process, parameters are established before the run of the optimization algorithm and are kept constant during the optimization. To find the set of "good" parameters, tuning experiments must be performed. However these experiments are computationally expensive since for each parameter setting, a complete optimization must be

[2] An international football field has in average an area equal to 7297m^2.

run. Consequently, Andersson *et al.* (2016) claim that it is not realistic to expect parameter tuning to be executed for every new algorithm and problem combination. Hence, it is normal to find certain recommended heuristics and (default) parameter values for a certain set of problems. These recommendations are normally established based on test functions such as constrained DTLZ1 and DTLZ2 (Deb *et al.*, 2002b). Nonetheless, it cannot be ensured that the default parameters are effective for a specific problem, especially to an applied problem such as the microgrid planning optimization problem.

In the context of this research, a simple methodology based on a *generate and test* principle for the evaluation of combinations of parameter values is implemented (Eiben and Smit, 2011). Therefore, a fixed set of parameter vectors is created during the generation step, and all the vectors are evaluated with the same number of tests (optimization run) during the test step. Test results are evaluated accordingly to an indicator such as *hypervolumen* indicator, and the best results give rise to the parameter array with the best performance.

In this dissertation, parameter tuning for NSGAII is performed and presented, while parameter tuning for the MOEA/D algorithm is performed and presented by Lopez Rivera and Rodríguez Bejarano (2019) and Rodriguez *et al.* (2020). The test CS1 is used for parameter tuning as it is described below, and the results extrapolated to the CS2. Particularities of the CS1 are described in Section 6.4.

6.2.1. Genetic operators parameter tuning

Generation of parameter vectors for tuning of the NSGAII

The NSGAII multi-objective optimization algorithm is based on a population-based metaheuristic with genetic operators. Within this framework, population parameters such as *population size* $\mathrm{N_{pop}}$ and *maximum number of generations* $\mathrm{N_{gen}}$, and parameters of the genetic operators such as crossover and mutation are tuned (Song, 2020; Deb *et al.*, 2002a). Regarding the genetic operators, the parameters below are selected according to Song (2020).

- Intermediate crossover ratio (CR).
- Scale parameter for the Gaussian mutation (standard deviation) (σ_S).
- Shrink parameter for the modification of the Gaussian mutation (SR).

Intermediate crossover creates two children from two parents. Song (2020) indicates that a CR between [0,1] creates a child between the parents. In this way, premature convergences may require CR > 1. The scale parameter (σ_S) determines the standard deviation of the random number generated in the Gaussian mutation. Furthermore, the shrink parameter SR is a scalar in the range [0,1]. Song (2020) describes that the shrink parameter decreases the mutation range while the optimization progress. Thus, SR $\in [0.5, 1.0]$ is normally used for

local search according to Song (2020). When there are problems with different local Pareto optimal sets, a large mutation range is required and a SR $\in [0, 0.5]$ is more convenient.
The parameter vectors for tuning are strategically set considering guidelines ofSong (2020) and Deb *et al.* (2002a) as CR $= \{0.5, 1.0, 1.1, 1.2, 1.3, 1.4\}$, $\sigma_S = \{0.04, 0.08,\ 0.10, 0.12, 0.16\}$ and SR $= \{0.0, 0.25, 0.5\}$. Consequently, 108 different parameter vectors are generated as a combination of all possibilities as in Figure **6-1**.

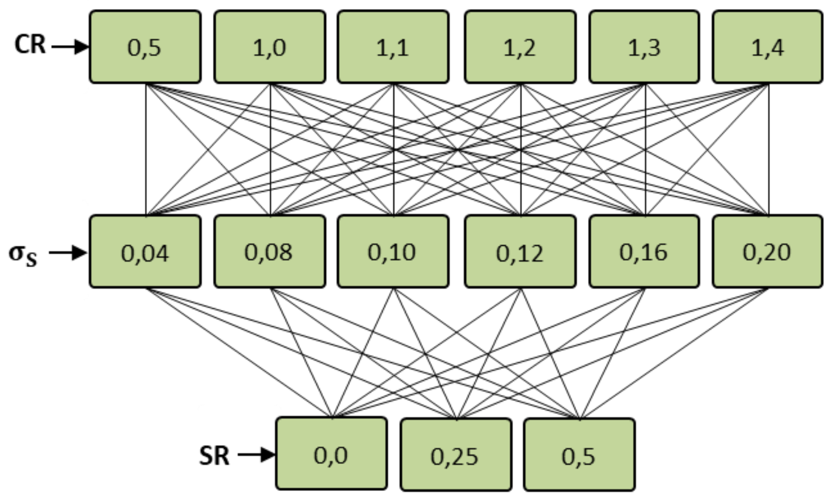

Figure 6-1.: Parameter tuning test vector generation

Regarding the population size and number of generations, the tuning task is treated separately from the genetic operators. For the genetic parameter tuning, a reduced population and number of generations are used (10% and 20%, respectively). For example, for an array of 500 individual and 100 generations, 50 individual and 20 generations are used for testing each of the parameter vectors, which lead to 108000 evaluations of the objective functions ($50 \times 20 \times 108$) in the tuning process. The limits of the decision variables were strategically selected based on the total load demand. The PG&E 69-bus has a total load demand of P=3802.19 kW (Refer to Section 3.4 and Appendix A). The limits are indicated in Table **6-2**, where the maximum total DERs' installed capacity is chosen for a maximum of 3 times the total load demand.

Test of parameter vectors for tuning of the NSGAII

The numerical results of testing the parameter arrays are analyzed in this part of the section to find a proper parameter setting. The first outcome leads to identify the limits of the searching space for all the parameter vectors in four different runs. This is visualized in Figure **6-2**.
It can be noticed in Figure **6-2** that all the tests converge to a similar search objectives

Table 6-2.: Standard DG unit sizes and optimization boundaries for CS1 parameter tuning

DG type / Case	No. Units	Lower boundary P_{lb} [**kW**]	Upper boundary P_{ub} [**kW**]
Discrete variables			
MT	5	0×35	10×35
WT	5	0×120	10×120
Continuous variables			
PV	10	0	100
BA	5	0	600
Buses for location			
MT,WT,PV,BA	$2, \ldots, 69$		

space. However, the average hypervolume indicator for each tested parameter array in the four runs is analyzed in the bar plot in Figure 6-4.

In this first phase of the parameter tuning approach, it is found that the solutions converge with a certain pattern in the hypervolume indicator [3]. For instance, solutions with scale parameter values under 0,10 do not present high hypervolume, while solutions over this value, independently of the intermediate crossover ratio, give rise, in average, to the highest values. These can be also visualized in Figure 6-2, where some maximum and minimum values in the objective functions are related to these aforementioned values. To select a set of candidate parameters for refinement, 10 highest hypervolume indicator values are chosen per each run. These values are shown in Figure 6-3.

From the results in Figures 6-4 and 6-3, the parameter test vector with the highest hypervolume indicator value and repeatability are highlighted and selected as possible candidates for further analysis. Therefore, the parameter test vectors number 36, 32, 13, 101, 70 and 102 are shown in Table 6-3. These are sorted from high to low hypervolume indicator.

Table 6-3.: Generation of parameters vectors

Test number	**36**	**70**	**13**	**32**	**102**	**101**
CR	1,0	1,2	0,5	1,0	1,4	1,4
$\boldsymbol{\sigma_S}$	0,2	0,2	0,16	0,16	0,12	0,12
SR	0,5	0,0	0,0	0,25	0,5	0,25
Average hipervolume indicator	0,0137	0,0133	0,0123	0,0122	0,0088	0,0083

[3] The hypervolume indicator value is estimated through 10000 uniformly distributed random points within the bounded hyper-cuboid by the reference point and dominated by the Pareto set.

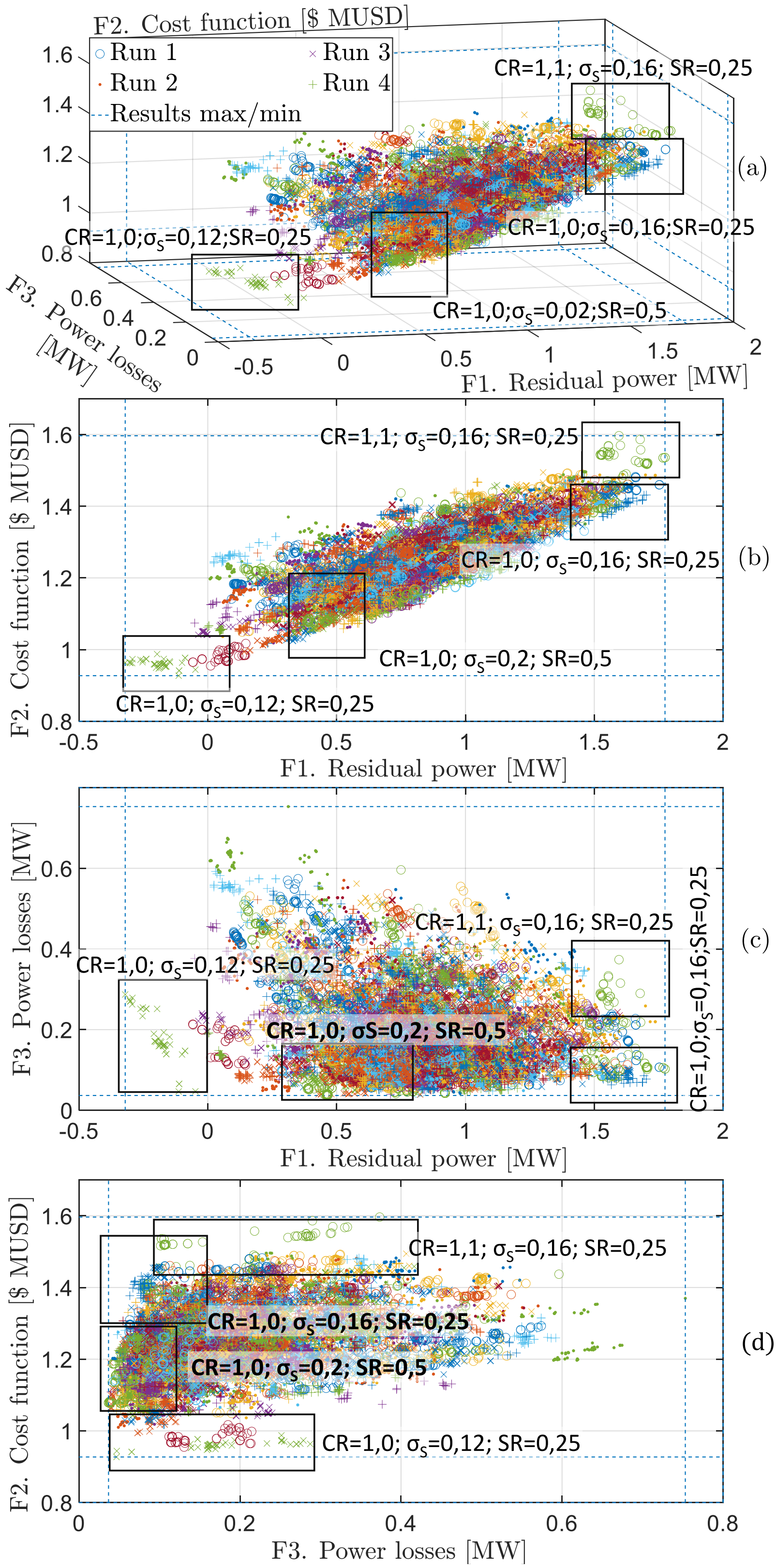

Figure 6-2.: Pareto fronts for the parameter test vectors - four runs

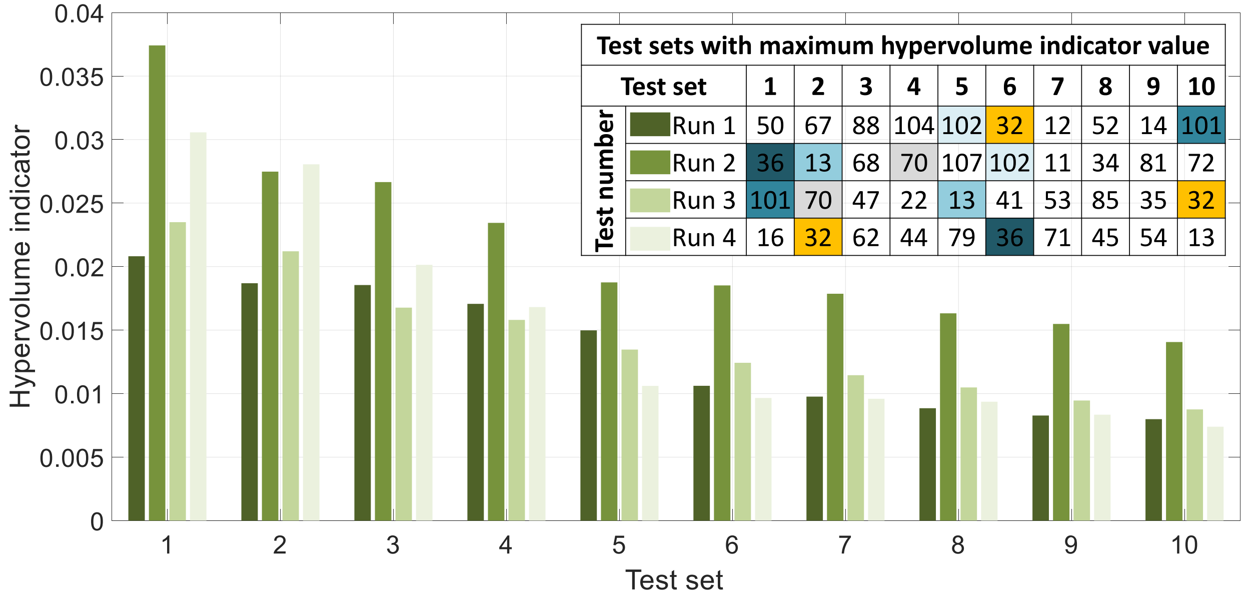

Figure 6-3.: Highest hypervolume indicator for the parameters test vectors in each run

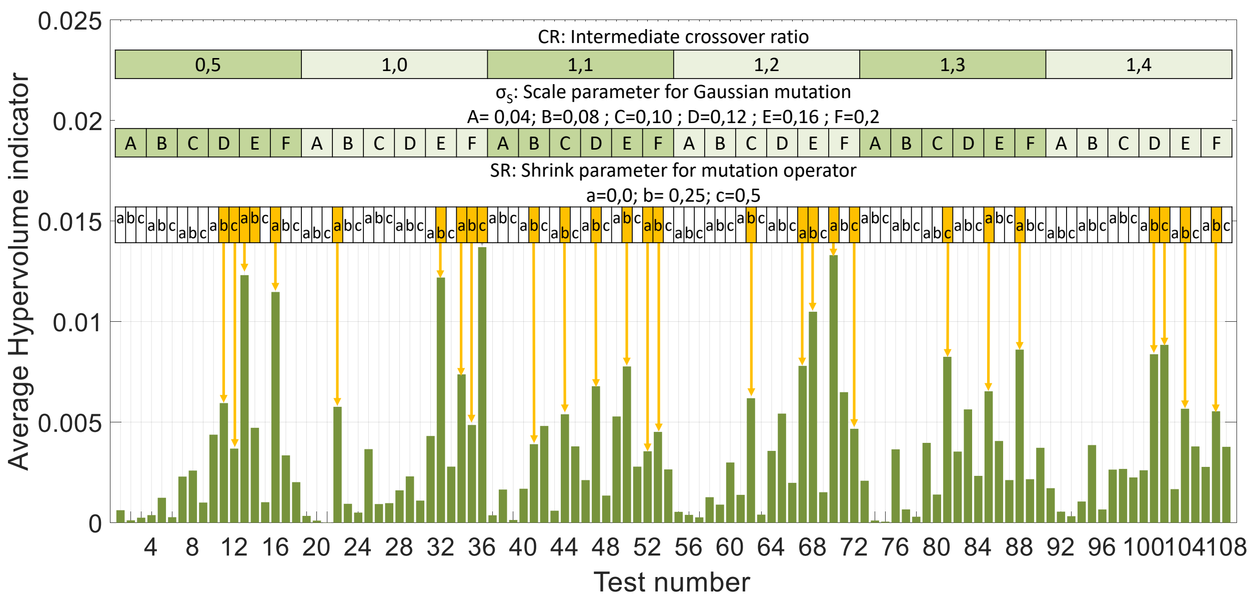

Figure 6-4.: Average hypervolume indicator for the parameters test vectors

From Table 6-3 and Figure 6-2, it seems that a parameter array with the highest scale parameter is associated with the highest hypervolume. Furthermore, combinations of the intermediate crossover ratio equal to CR=1,1 and CR=1,2 lead to the maximum and minimum values of the objective functions. However, it is still not possible to claim that these parameter arrays are convenient for solving the microgrid planning problem. This can be a consequence of either the number of functions evaluations and/or the decision variables

limits.
Therefore, the next phase in the parameter tuning process is to define the minimum number of function evaluations in the optimization process and variables limit sensitivity for further parameter refinement. For that purpose, the highest hypervolume indicator (Test number 36) is chosen as a preliminary parameter selection. Afterward, a final parameter tuning refinement is performed to define a final parameter configuration.

6.2.2. Analysis of the decision variables limits effect in terms of DERs capacity

It was presented in Chapter 4 the composition of the decision variables vector as well as constraint functions as part of the microgrid planning optimization problem definition. Due to variable limits constrain by themselves the feasible searching space, at this point, the effect of the upper and lower limit of the variables-set vector regarding the DERs' capacity is reviewed.
It is clear that POMMP and POMMP2 are intended to optimally size and locate DERs in order to plan microgrids with the capacity to provide AS to the main grid. Hence, the total capacity limit for all DERs must be higher than the maximum demand of the base case. Therefore, considering the total load for the PG&E 69-bus test base system of the CS1, nine different upper limit values are reviewed, Table **6-3**. A maximum number of function evaluations of 50000 (500 individuals and 100 generations) and the preliminary chosen genetic operator parameters of vector number 36 are used. Numerical results of the simulations for the configurations with limits 1 to 9 are shown in Figure **6-5**.
The results in Figure **6-5** offer interesting information regarding the planning problem solution by the proposed methodologies. Firstly, there is a lower limit regarding the upper boundary for the decision variables set of the DERs' capacity. This characteristic could be found with the Pareto set outcome for the "Limit 1", "Limit 2" and "Limit 3". In these cases, despite the upper boundary rising to a possible maximum installed capacity of 1,35 times the maximum active power load demand of the base network, all the solutions converge to a narrow surface in the searching space. Three main reasons are given for this condition:

- The installed capacity includes dispatchable generation, non-dispatchable generation and ESS. Therefore, actual available output power depends on the stochastic nature of non-dispatchable generation and the charging/discharging cycles of the batteries. Thus, the installed capacity does not represent any more an effective reference for the maximum available generation power.

- The reactive power capacity is limited to the conventional rotating machine-based DG technologies and reactive power dispatch assumptions for the non-conventional electronically interfaced DG units and ESS. Therefore, the microgrid's performance

Table 6-4.: Standard DG unit sizes and variables limits effect analysis

Variables limits case test	**Type of variable set**				**Maximum instaled capacity [kW]**	**Ratio of peak active load of base case**
	Discrete variables		**Continuous variables**			
	DG technology					
	MT	**WT**	**PV**	**BA**		
	Number of allowed buses with the DER technology*					
	5	5	10	5		
Lower boundary - P_{lb} [kW]						
Limits 1-9	0×35	0×120	0	0	0	0
Upper boundary - P_{lb} [kW]						
Limit 1	5×35	5×120	50	150	5125	1,35
Limit 2	10×35	10×120	50	150	9000	2,37
Limit 3	10×35	10×120	100	600	11750	3,09
Limit 4	15×35	15×120	75	225	13500	3,55
Limit 5	20×35	20×120	200	1200	23500	6,18
Limit 6	30×35	30×120	300	1800	35250	9,27
Limit 7	40×35	40×120	400	2400	47000	12,36
Limit 8	50×35	50×120	500	3000	58750	15,45
Limit 9	70×35	70×120	700	4200	82250	21,63
Buses for all DER technologies location						
$2, \ldots, 69$						

* Maximum number of buses in the network that can admit the DER technology

at each time step along the planning horizon is affected by the actual reactive power capacity and bus voltage levels.

- The residual power capacity is one of the objective functions and the main goal for the POMMP and POMMP2 methodologies. The minimum AS bid capacity is constrained as part of the optimization definition. Small capacities could present limitations because of the constraint.

In these three limit cases, the Pareto set outcome with the values of "Limit 1" cannot get solutions with positive reserve power. Contrary, solutions with "Limit 2" and "Limit 3" converge to the lowest area for the residual power F1 and cost function F2 (Figure 6-5 (b)), which is the result when the decision variables of capacities reach the upper boundary values of the DER technologies. For this reason, the variations in the power losses are given only by the different locations of the DER technologies for each solution in the Pareto solutions

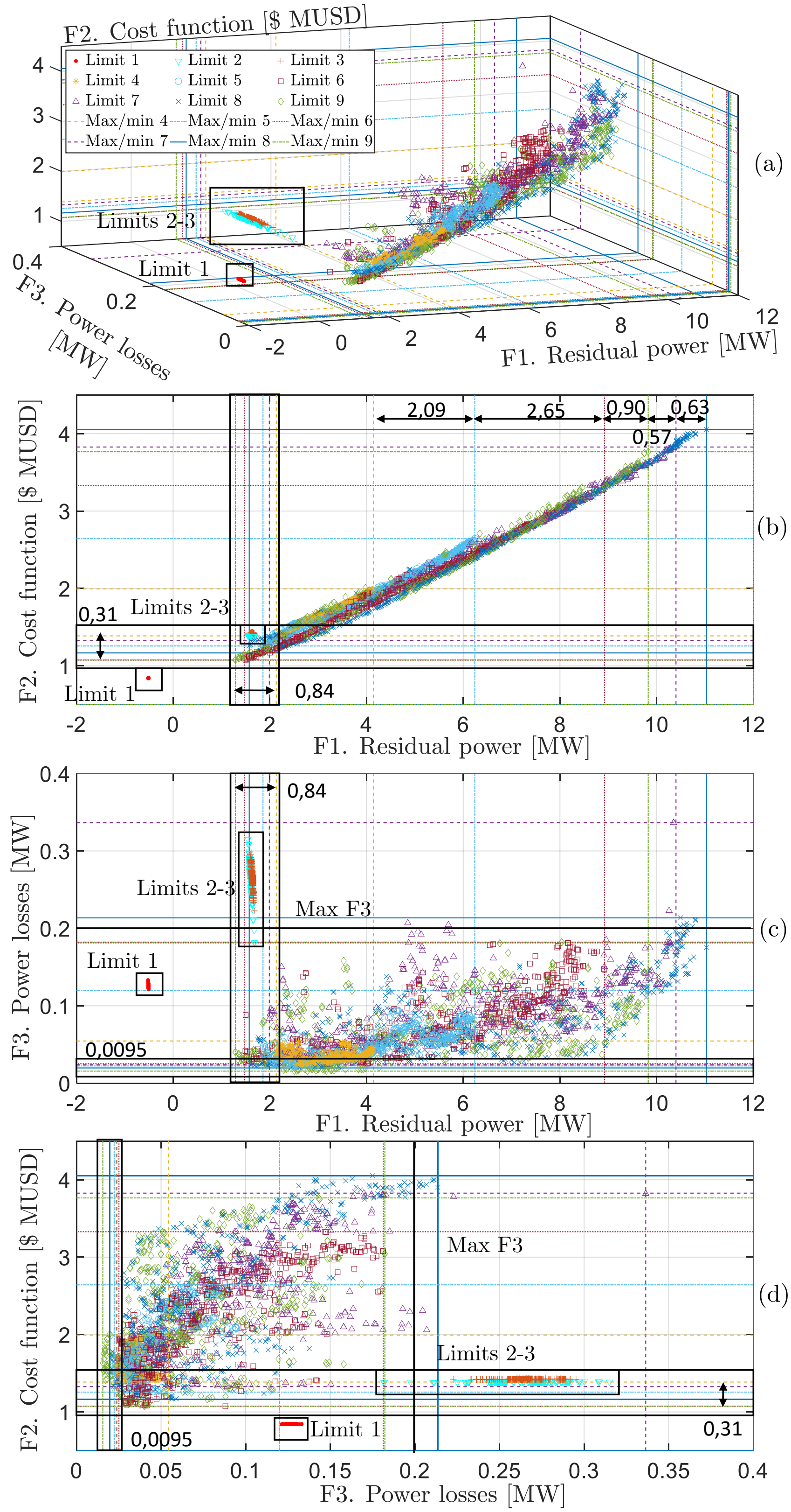

Figure 6-5.: Pareto fronts for different DERs' decision variables limits

(Figure 6-5 (c)-(d)).

Secondly, over a lower limit between 3,0 and 3,5 times the total active power of the base case, independently of the decision variables limits, all optimal Pareto set converge to the relatively same region in the feasible objective space. However, the capacity limits in the decision variables vector, as expected, affect the maximum reached values of the objective functions as the maximum capacity limit increases. This feature can be seen in Figure 6-5 (b)-(d).

The maximum values of the F1 residual power increases as the upper boundary is higher. Consequently, the F2 microgrid's cost and F3 microgrid's power losses increase as well. Furthermore, it can be noticed that the highest increases are reached between the lower capacity limits range. For example, the difference is higher (2,09 MW) between the "limit 4" and "limit 5" with an increment of 2,63 of the capacity ratio, while lower (0,63 MW) between "limit 7" and "limit 9" with an increment of 9,27 of the capacity ratio. This last particularity is even more visible in the objectives functions F2 and F3. For instance, maximum power losses for the Pareto solutions of the "limit 7", "limit 8" and "limit 9" in Figure 6-5 (c) converge mostly under a 0,2 MW value (line Max F3). As a conclusion, it can be said that the upper boundary of the capacity decision variables vector set affects the maximum limit of the objective function. However, there is an upper limit in the residual capacity for further increments.

Thirdly, the lower values for all the Pareto solutions set converge to a common boundary in the feasible objective space. This can be seen in Figure 6-5 (b)-(d), where the highest difference is 0,84 MW among the minimum values of the F1 residual power, 0,31 $ MUSD for the values of the F2 cost function and 9,5 kW for the values of the F3 power losses. The result is especially relevant for the F2 and F3 objective functions since these are minimization objectives. Furthermore, notice that the Pareto solutions for the optimization with Limit 1, Limit 2 and Limit 3 in Table 6-4 converge to these lower boundaries. In these three cases, the total added rate capacity of the upper boundary of the decision variables have a ratio lower than 3,5 times the total added peak demand of the base case system.

To sum up, it can be concluded the planning methodology is sensitive to the limits of the decision variables set of the DER's capacity. For example, it is found that there is a minimum value for the upper boundary of the variables that lead to properly explore and exploit the feasible search space and reach desirable ranges for the Pareto solutions. Furthermore, the upper boundary affects mainly the maximization of the F1 residual power, where the highest increase in the maximum reached values of the objective functions is found for upper boundaries between 3 and 12 times the base case active load. Higher upper boundaries give rise to smaller increases in the maximization of the F1 residual power. Finally, the minimum reached values of the functions in the feasible objective space are less affected by the upper boundary decision variables limit. In this case, the three objective functions lead to solutions with similar minimum values, which is especially relevant for the minimization functions of cost F2 and power losses F3.

6.2.3. Analysis of the number of function evaluations for solving the optimization problem

As mentioned above, the number of individuals of the population and the maximum number of iterations is treated separately from the genetic operators' parameters. Within this framework, the number of individual and generations are evaluated and chosen conveniently to complete more than 10000 and up to 50000 evaluations of the objective functions. This range of evaluations is defined based on conventional practices in literature and usual competition guidelines of the *IEEE PES Working Group on Modern Heuristic Optimization* for evaluating the performance of modern heuristic optimizers on power systems problems [4].

Considering the CS1 and variables of the "limit 5" configuration (Table **6-4**), the selected maximum number of function evaluations (50000) is configured in an array of 500 individuals and 100 generations for simulations. Furthermore, ten different runs are performed. The convenient number (trade-off) of function evaluations for solving the microgrid planning problem is defined by analyzing the changes of the maximum and minimum values of the objective functions and the hypervolume indicator over each generation. The Pareto solutions are shown in Figures **6-6** to **6-9**.

Results in Figures **6-6** to **6-9** show that the convergence is mainly determined by the power losses of the solutions. In this way, after 25 generations more than 90% of the individuals of the Pareto set converge to the minimum power losses value in the objectives space, Figure **6-6** (a) and (d). However, the maximum values for the residual power are mainly achieved in consecutive generations. For example, solutions with maximum residual power for the generation 25 gives rise to a value of 4,45 MW, Figure **6-6** (a) and (c), while generations 50, 75 and 100 give rise to values of 5,30 MW, 5,92 MW and 6,23 MW, respectively, Figures **6-7**, **6-8**, **6-9** (a) and (c).

On the contrary, after the generation 25, the maximum power losses for generations 25, 50, 75 and 100 are 0,24 MW, 0,11 MW, 0,12 MW, 0,12 MW, respectively, Figures **6-7**, **6-8**, **6-9** (a) and (d). This can be more precisely visualized in Figures **6-10** and **6-11**.

Values are normalized as a percentage of the highest maximum values of the respective objective functions for all generations. It can be concluded from Figures **6-10** and **6-11** that 25000 (e.g. 500 individuals, 50 generations) function calculations can offer a "good" enough approach solution to the Pareto optimal solution. However, considering the variation in the hypervolume indicator and minimum values of the objective functions, smaller variations in the values are achieved after generation 70, which leads to 35000 function calculations.

[4] E.g. 2017 Competition on Evaluating the Performance of Modern Heuristic Optimizers on Smart Grid Operation Problems and 2020 Competition on Emerging heuristic optimization algorithms for expansion planning and flexibility optimization in sustainable electrical power systems considering uncertainty.

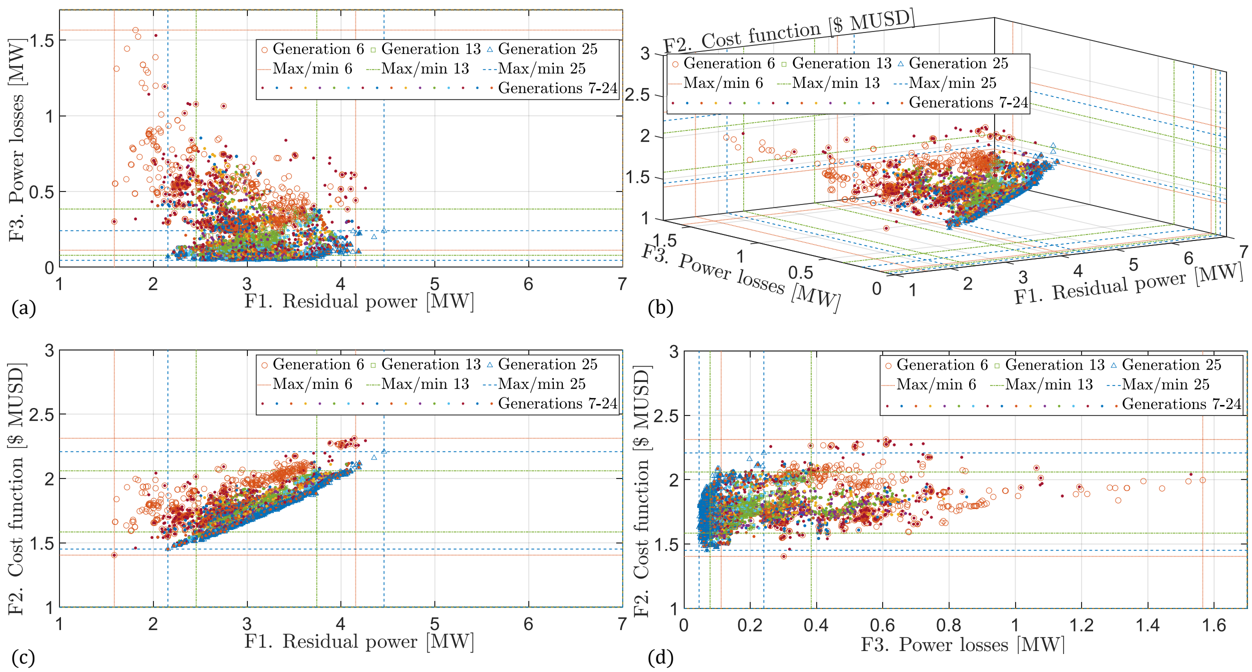

Figure 6-6.: Pareto fronts for 500 individuals, 100 generations. Generations 6 to 25

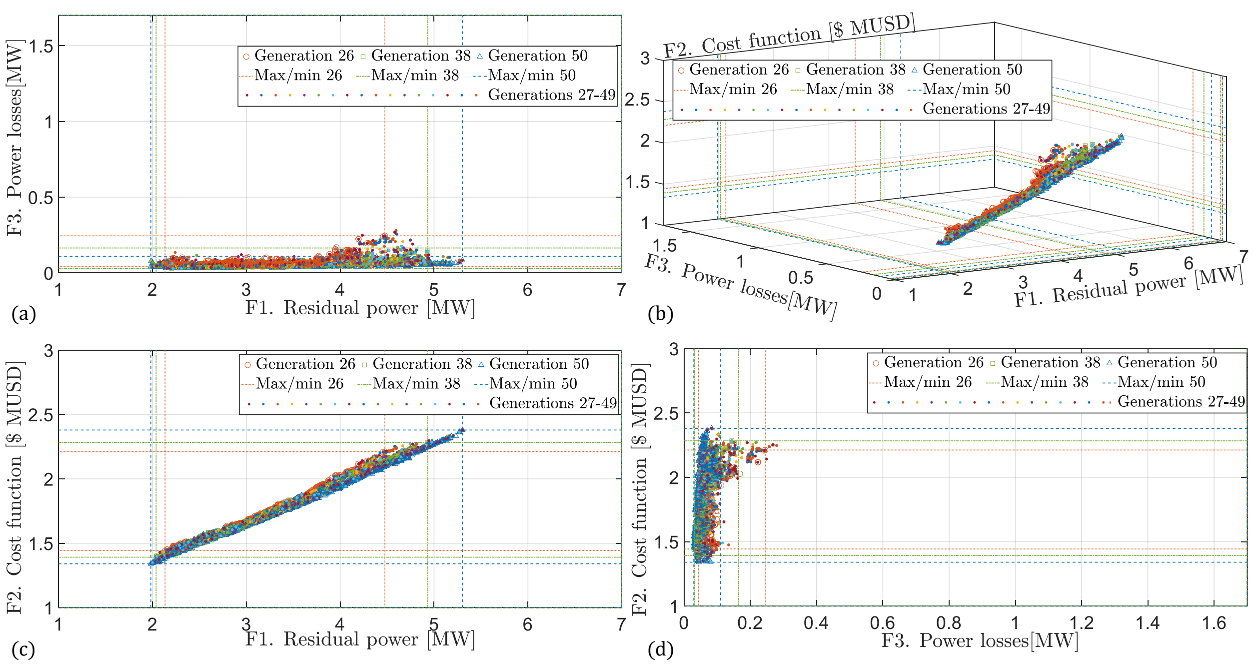

Figure 6-7.: Pareto fronts for 500 individuals, 100 generations. Generations 26 to 50

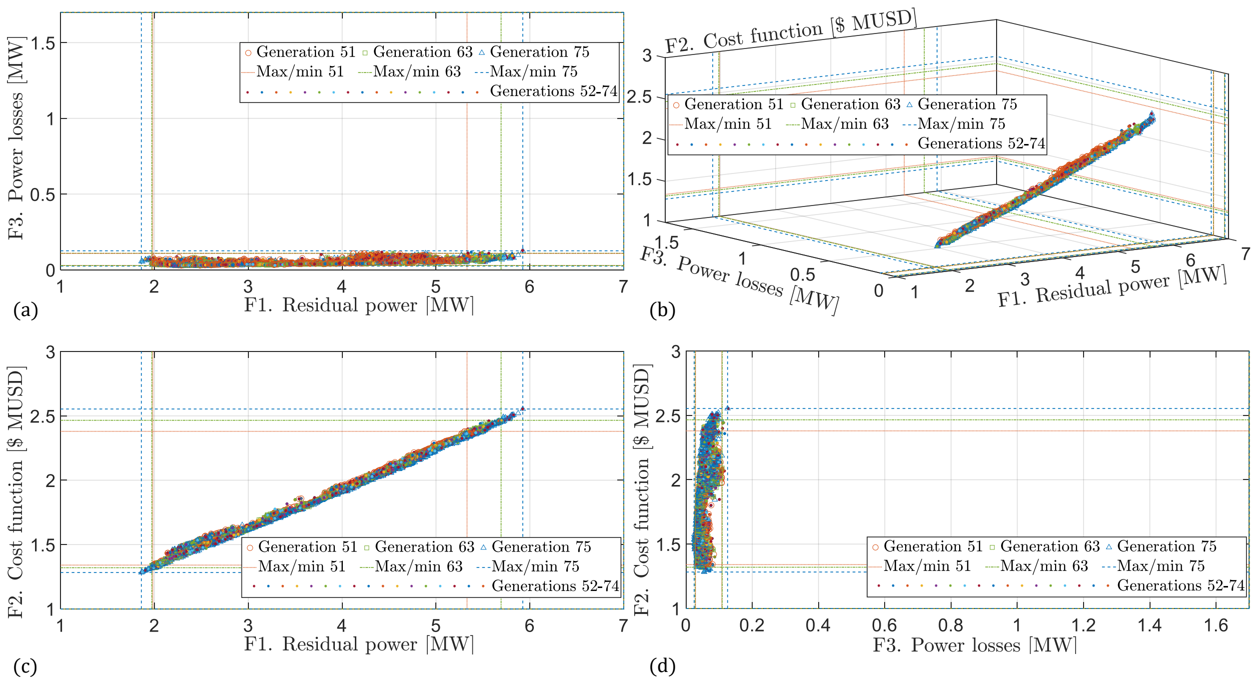

Figure 6-8.: Pareto fronts for 500 individuals, 100 generations. Generations 51 to 75

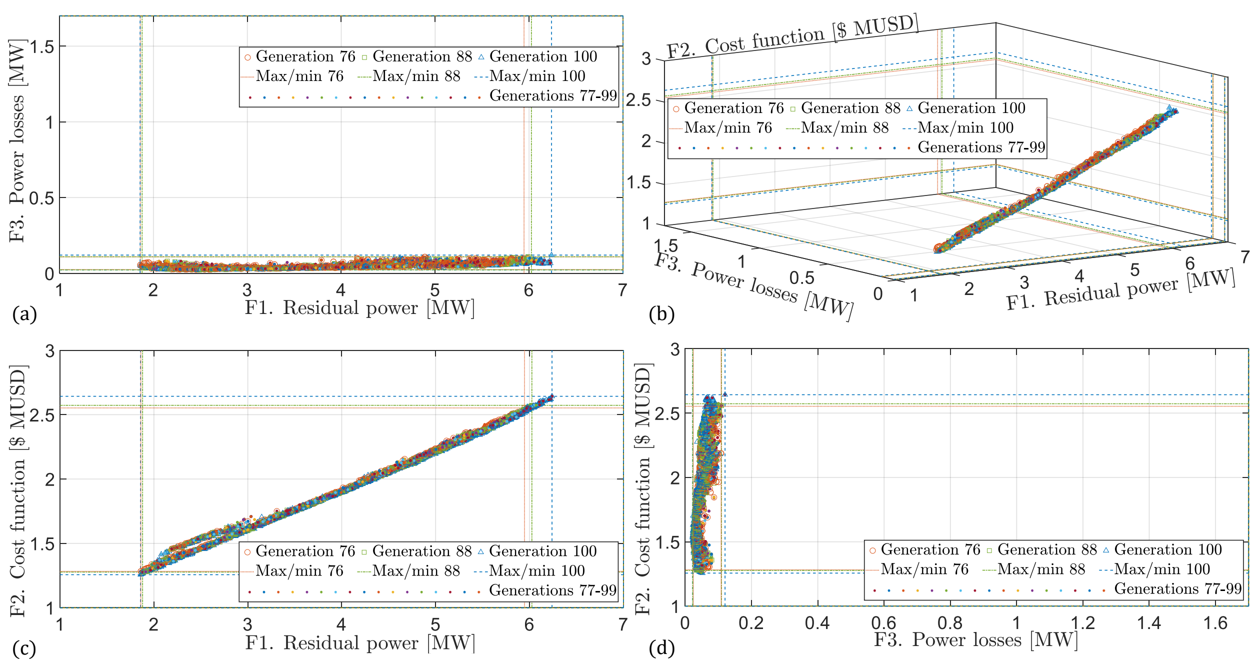

Figure 6-9.: Pareto fronts for 500 individuals, 100 generations. Generations 76 to 100

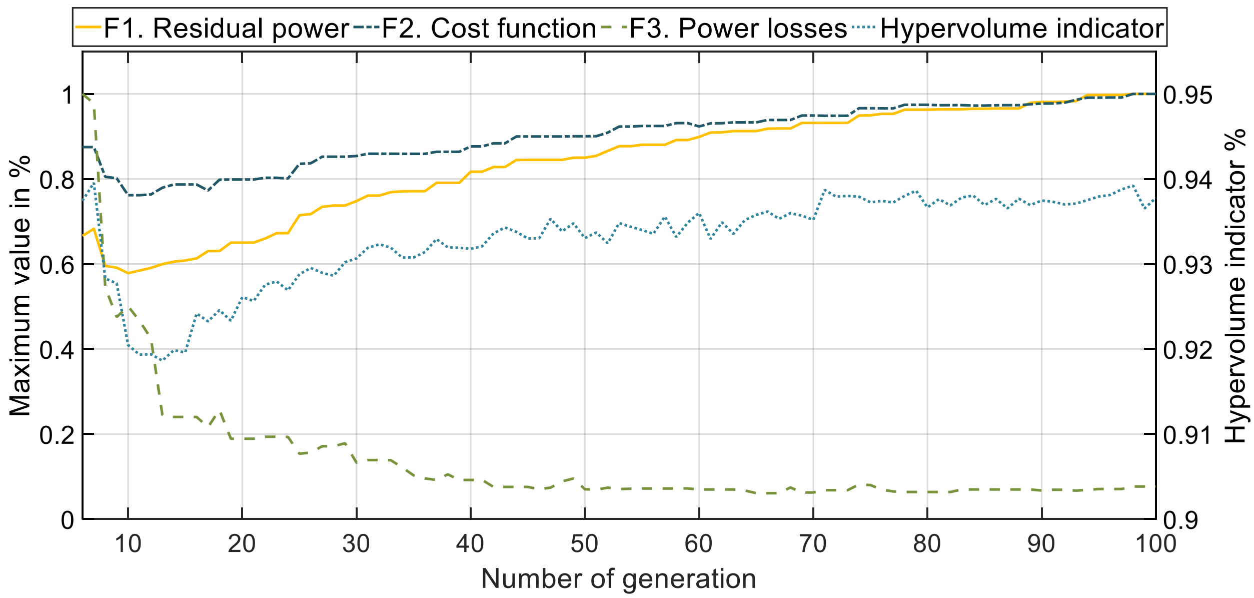

Figure 6-10.: Maximum objective function values and hypervolume indicator for each generation

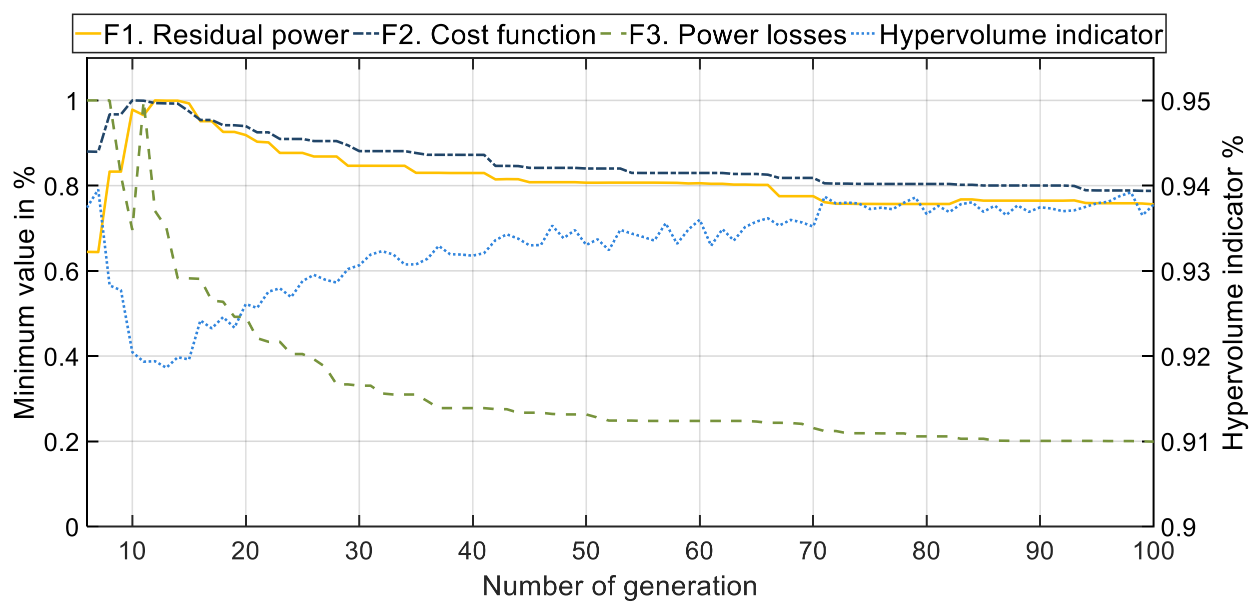

Figure 6-11.: Minimum objective function values and hypervolume indicator for each generation

The simulations were repeated 10 times with 500 individuals, and the Pareto solutions for the generation number 50, 70 and 100 are shown in Figure **6-12**.

The box plots in Figure **6-12** display five-number summary of each objective function of

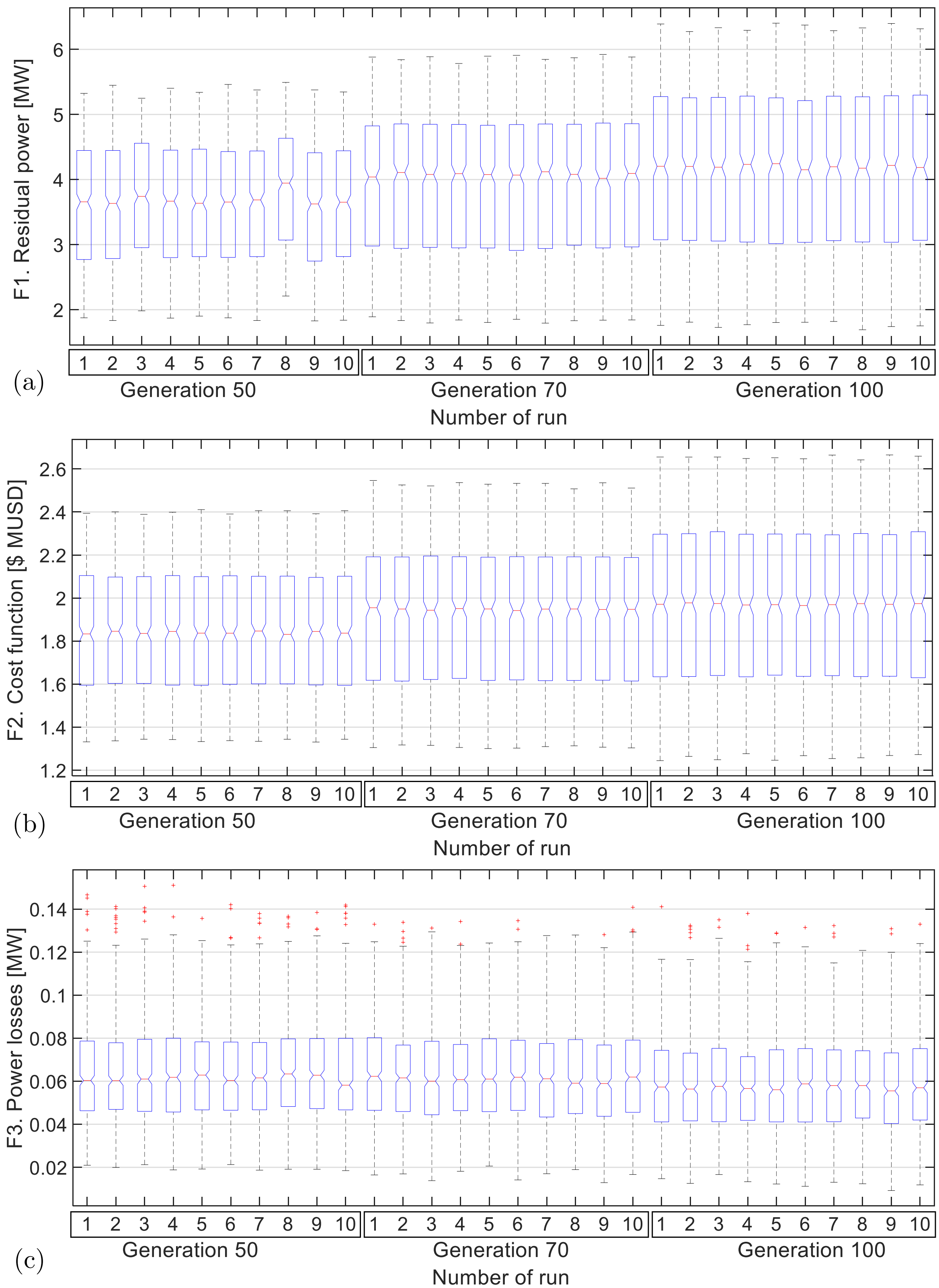

Figure 6-12.: Repeatability analysis for objective functions in the Pareto set

the Pareto set of data. The five-number summary is the minimum, first quartile, median, third quartile, and maximum values for the objective function values. On each box, the central mark indicates the median (50th percentile), and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the '+' symbol. Furthermore, two medians are significantly different at the 5% significance level if their intervals do not overlap. In the box plot, the interval endpoints are represented by the extremes of the notches or the centers of the triangular markers around the median value.

Correspondingly, box plot data show that the median value of every objective function does not differ significantly among individual runs of each generation. Furthermore, since the notches in the box plots of each generation overlap, it can be concluded, with 95% confidence, that the true medians do not differ from these values. However, notches of the solutions of 50 generations do not overlap with the notches of generation 70 and 100, which lead to conclude, with 95% confidence, that the media will diverge after 25000 and until approximately 35000 function calculations. Notice that the median and notch of generations 70 and 100 overlays.

It can be noticed that minimum values for the three objective functions remain relatively similar for the three generations of each objective function. On the contrary, the maximum values depend on the generation number mainly for the objective functions F1 and F2 (Figure **6-12** (a)-(b)). However, it is also visible that the 75% of the values will be over 3,0 MW in the residual power case, and under 2,3 $ MUSD in the cost function case.

To sum up, it can be said from numerical results that the planning methodology gives rise to repeatable results with median values with 95% confidence. Furthermore, 2500000 function calculations can offer optimal Pareto solutions with a coverage of around 75% in the objective function F1, and more than 75% for objective functions F2 and F3. However, minimum 35000 function calculations are recommended to solve the microgrid planning problem with POMMP or POMMP2 since the coverage of values will cover more than 75% of the solutions with 50000 function calculations.

6.2.4. Refinement of the genetic operator parameter tuning

Considering the preliminary genetic parameter tuning, decision variables boundaries and number of function evaluations, a refinement of the genetic operator's parameter tuning is executed in this part of the analysis. For this purpose, two final evaluations are managed: 1) test parameter vectors used in the preliminary tuning 2) pre-selected parameter vectors with a higher number of function evaluations. For that purpose, the parameter in Figure **6-1** and the decision variables boundaries with the "limit 5" configuration of Table **6-3** are used. A reduced population of 50 individuals and 25 iterations are used for the analysis. The parameter tuning output is shown for all parameter vector in Figure **6-13**.

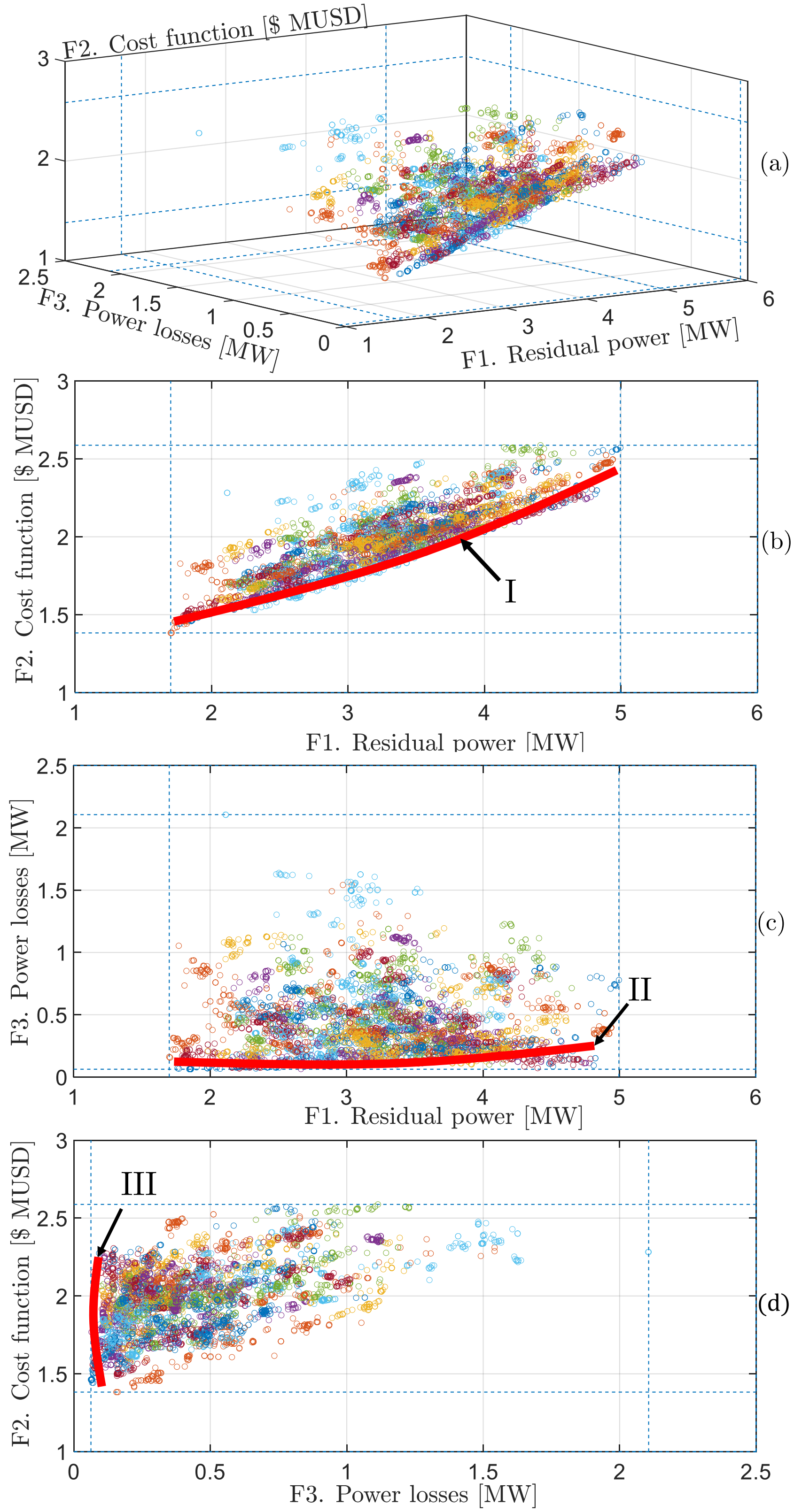

Figure 6-13.: Pareto solutions for different parameter tuning vector sets

Results in Figure 6-13 follow the behavior seen in the former analysis of the optimization performance in terms of the decision variables boundaries and the number of iterations in Figures 6-5 and 6-6, respectively. This expected solution for a higher population and the number of generations is marked by the solid lines I, II and III in Figure 6-13. Additionally, it is also possible to identify different solutions out of the expected convergence region for the used number of generations. Therefore, the maximum and minimum values for the objective functions are identified for each parameter test vector. Afterward, the parameter set vectors with closer solutions to the expected fronts are evaluated in terms of the hypervolume indicator.

In this particular case, convergence can be conveniently assessed based on the third objective function F3 of power losses. Consequently, Figure 6-14 presents the hypervolume value for each parameter test vector together with the maximum and minimum achieved value of power losses.

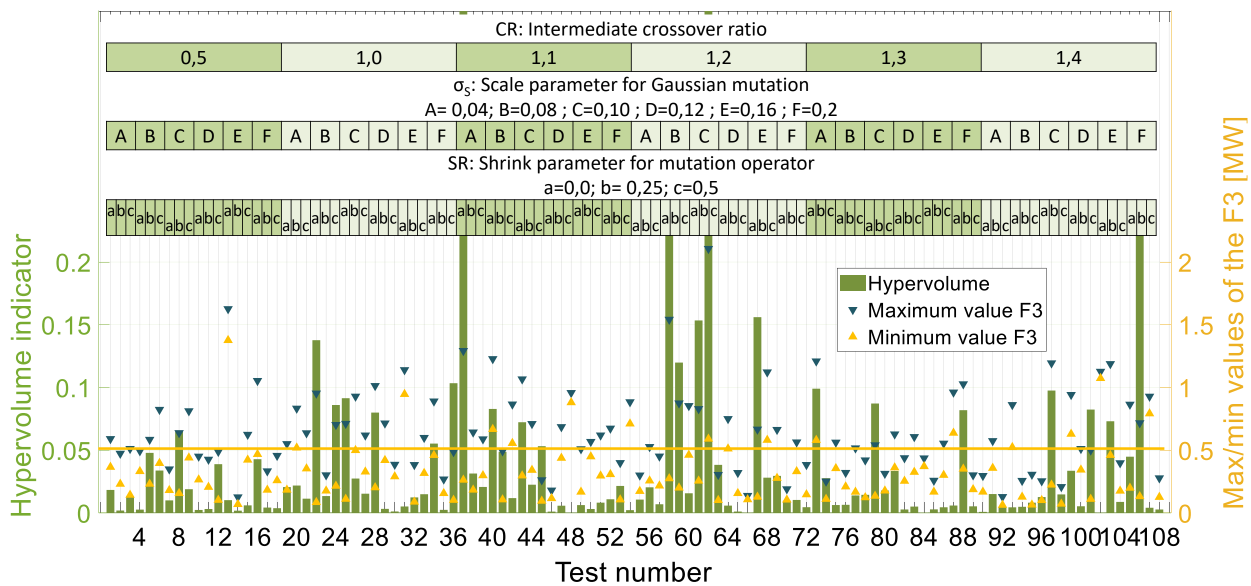

Figure 6-14.: Hypervolume indicator for the parameters test vectors and the minimum values of the F3. power losses

To select a set of candidate parameter configuration, the results in Figures 6-6 (a) and 6-7 (a) are used as reference. These showed that the third objective function F3 of Pareto optimal set converges with values under 0,5 MW. Therefore, 20 solutions with a maximum value of F3 under 0,5 MW are selected and organized based on their hypervolume value in Figure 6-15.

A final refinement simulation test is run for the first 6 parameters. In this case, 500 individuals and 25 generations are used. The results are shown in Figure 6-16.

Results in Figure 6-16 show the effect of the parameter configuration on the Pareto so-

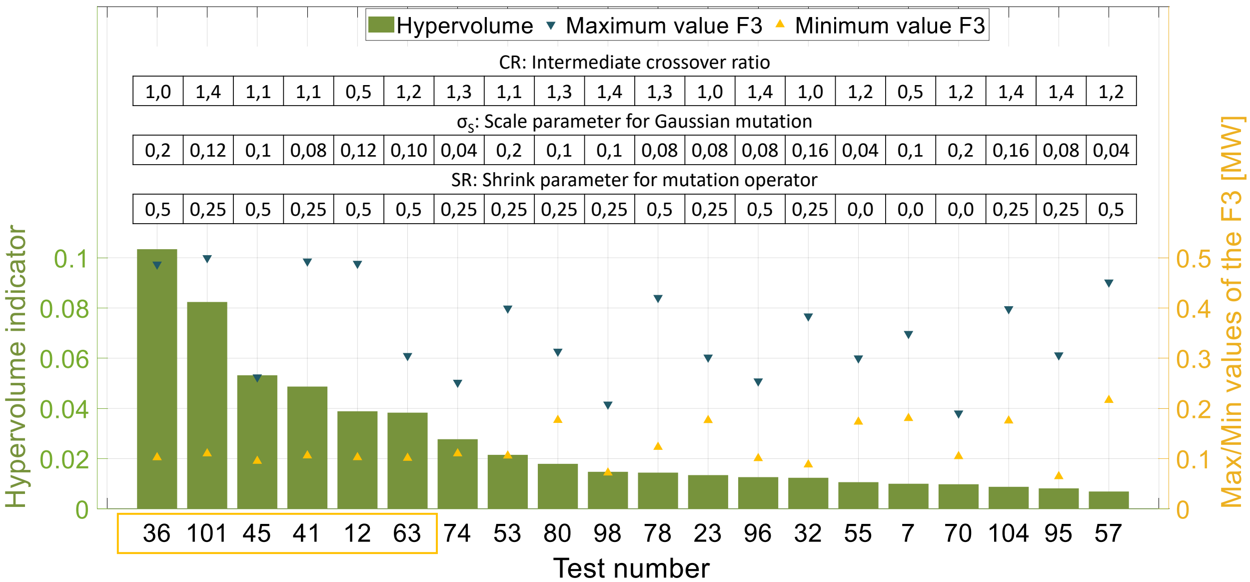

Figure 6-15.: Selection of parameter test vectors

lution set. It is found that the parameter test vector number 45 and 12 have a deficient performance to reach maximum and minimum values in the objective function compared with the other parameter configurations. On the contrary, solutions 101 and 36 attain the highest hypervolume indicator with values of 0,0798 and 0,1052, respectively. Additionally, the Pareto solution for the parameter test vector number 36 get the minimum values in the objective function F3 of power losses (0,0327MW) compared with the values for the other analyzed Pareto sets. Solutions with parameter configurations number 41 and 63 present similar performance with hypervolume values of 0,0485 and 0,0376, respectively. Furthermore, these two solutions achieve the highest values together 101 in the objective function F1 of residual power.

To conclude the genetic operator's parameter tuning, the performance of the solutions depends strongly on the whole combination of parameters. In this particular case, the parameter configuration 36, 101, 41 and 63 can be interchanged to achieve similar Pareto solution sets. Therefore, configuration 36 of CR=1,0, $\alpha_s = 0,2$ and SR=0,5 is used for the simulations presented in the following sections with the optimization algorithm NSGAII.

6.3. Multi-criteria decision making strategy for the optimization problem solution

For the numerical analysis of the solutions of the two case studies, CS1 and CS2, with POMMP and POMMP2 methodologies, we take the role of decision-makers to apply the multi-criteria decision-making approach described in Chapter 4. Therefore, the objective

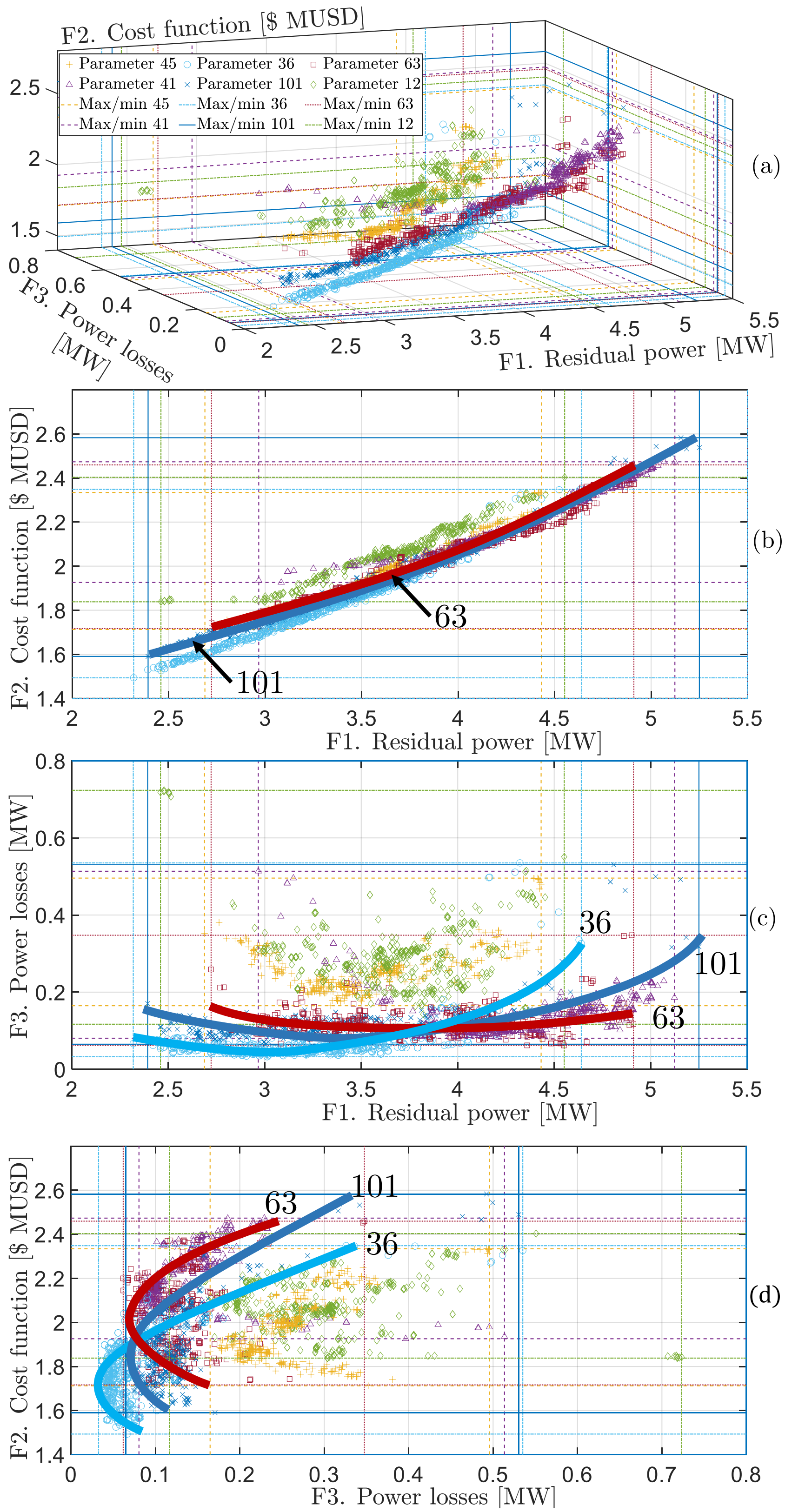

Figure 6-16.: Final Pareto solutions for selected parameter tuning vector sets

functions relevance order has been defined as:

1. F1: Residual active power in grid-connected mode for the AS provision.

2. F2: Operating and profit cost of the Microgrid

3. F3: Annual power losses

Following the Saaty scale in (Saaty, 2008), the comparison matrix for the objective functions that have been defined by the decision-maker for the two study cases is shown in equation (6-1). Accordingly, an intensity of importance 1 (equal importance) is chosen for two criteria (objective functions) that contribute equally to the main objective of the AHP; 3 (moderate importance) is for a judgement slightly favoring one criteria over another; and 5 (strong importance) is for a judgement strongly favoring one criteria over another.

$$B = \begin{array}{c c} & \begin{array}{ccc} F1 & F2 & F3 \end{array} \\ \begin{array}{c} F1 \\ F2 \\ F3 \end{array} & \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \end{array} = \begin{array}{c c} & \begin{array}{ccc} F1 & F2 & F3 \end{array} \\ \begin{array}{c} F1 \\ F2 \\ F3 \end{array} & \begin{bmatrix} 1 & 5 & 3 \\ 1/5 & 1 & 3 \\ 1/3 & 1/3 & 1 \end{bmatrix} \end{array} \tag{6-1}$$

The comparison matrix for the Pareto solutions set (alternatives) has been built assigning all 9 values of the Saaty's scale. First, the number of alternatives will be equivalent to the chosen number of individuals (solutions) in the population. Second, to assign the Saaty's scale, the solutions are organized in descending or ascending order depending on whether it is a maximization or minimization objective. In this case, the *residual active power in grid-connected mode for the AS provision* is organized in descending order, the *operation and profit cost* is organized in ascending order and the *annual power losses* is organized in ascending order as well.
Afterwards, the whole Pareto solutions set is divided and rounded in 9 different Saaty's groups, balancing the division based on the closest multiple of 9 and assuming the integer left over (remainder) in the last scale's group. In this instance, considering the Pareto optimal set of 500 individuals in Section 6.2, the closest multiple of 9 is 504. Hence, the solutions' grouping for the Saaty's scale assignation will be organized as in Table **6-5**.

Table 6-5.: Assignation of Saaty's scale for a population of 500 individuals

Saaty's scale								
1	2	3	4	5	6	7	8	9
Pareto optimal set								
$1-56$ 56+	$57-112$ 56+	$113-168$ 56+	$169-224$ 56+	$225-280$ 56+	$281-336$ 56+	$337-392$ 56+	$393-448$ 56+	$449-500$ 52+

In this example, a comparison matrix $S_{500\times500}$ is generated as part of the procedure described in Chapter 4. It is important to clarify that the objectives' relevance order can be modified based on other preferences and/or requirements. The results of the decision making by AHP are used in the following sections for the selection of single solutions for their analysis.

6.4. Case study 1 - (CS1): Microgrid planning for the PG&E 69-bus medium voltage distribution network

The CS1 is defined based on the PG&E 69-bus base case. The PG&E 69-bus base case is a MV radial-based passive distribution network with seven laterals and represents a portion of an actual PG&E distribution network in the USA. The details of the base case are described by Savier and Das (2007) and Baran and Wu (1989), and the adaptation was made based on (Arefifar and Mohamed, 2014b,a) as shown in Figure **6-17**.

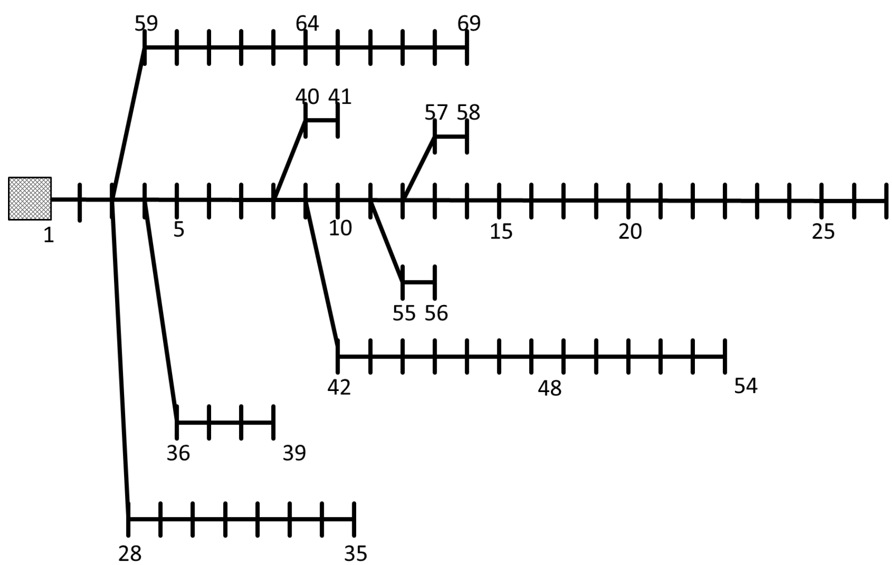

Figure 6-17.: Test system PG&E 69-Bus (not to scale) for the Case Study 1, adapted from Contreras *et al.* (2019)

The base power and voltage of the system are set to be 10 MVA and 12.66 kV. The total load for the base case configuration is P=3802.19 kW, and Q=2694.60 kVAr (Baran and Wu, 1989). The load data are detailed in Appendix A of this dissertation.
Two scenarios are proposed for testing POMMP in the CS1:

- **Scenario 1:** Microgrid planning under PJM market conditions
- **Scenario 2:** Networked planning under CAISO market conditions

In both scenarios, a planning horizon of one year with time-steps of one hour and three typical days per month are embraced according to the strategy described before.

6.4.1. Decision variables limits and particular parameters

The decision variables boundaries and planning parameters for the CS1 are adopted from the information and results in Sections 6.1 and 6.2. In consequence, the decision variables limits are defined as the limit configuration 5 in Table **6-4**. Furthermore, a maximum number of function evaluations of 50000 is used based on 100 generations and 500 individuals, and finally, AHP is implemented to select a single solution considering a trade-off based on the preference order of F1, F2, and F3.

6.4.2. Scenario 1: numerical results for the PJM market with POMMP methodology

The results for the PJM market are shown in Figure **6-18**. Lines I, II and III highlight the convergence boundary for each of the objective functions. It can be noticed that depending on the DERs' capacity and location solution, the microgrid for the PG&E 69-bus can be planned with the capability of delivering a residual power between 1,85MW and 6,23MW in average per each hour of a typical day, i.e., solutions **S01** and **S03**, respectively, in Figure **6-18** (a) and (d).

Solutions show a range of possible microgrid designs, whose microgrid cost can increase from 1,25 million up to 2,64 million, with a residual capacity for the AS provision and market participation up to 6,23MW and power losses between 22,26kW and 120,1kW. The selection of a solution would lead to a trade-off among the objective functions. For example, the solution with minimum average hourly power losses (22,9kW) is achieved for a microgrid with a residual power capacity of 2,46MW and an annual cost of 1,53 $MUSD, i.e., point **S02** in Figure **6-18** (c) and (d).

It is relevant to highlight the benefits of an *a posteriori* analysis of the optimal Pareto solutions set. For example, it is found that a higher penetration level of DERs has an impact on the power system losses. For this case study, the average hourly power losses decreases in the microgrid as DERs residual power increases (DERs penetration level). However, this behavior is maintained up to an inflection point around **S02**, where the power losses start increasing as residual power continues increasing. For a practical problem, such as the microgrid planning, this kind of behavior is not possible to know *a priori* since the final shape of the feasible objective space and Pareto solutions borders are also unknown.

The POMMP methodology ends with the selection of a single solution based on AHP. In the first iteration of the AHP, nine final solutions share the same highest-ranking R_p. These solutions are shown in Table **6-6**.

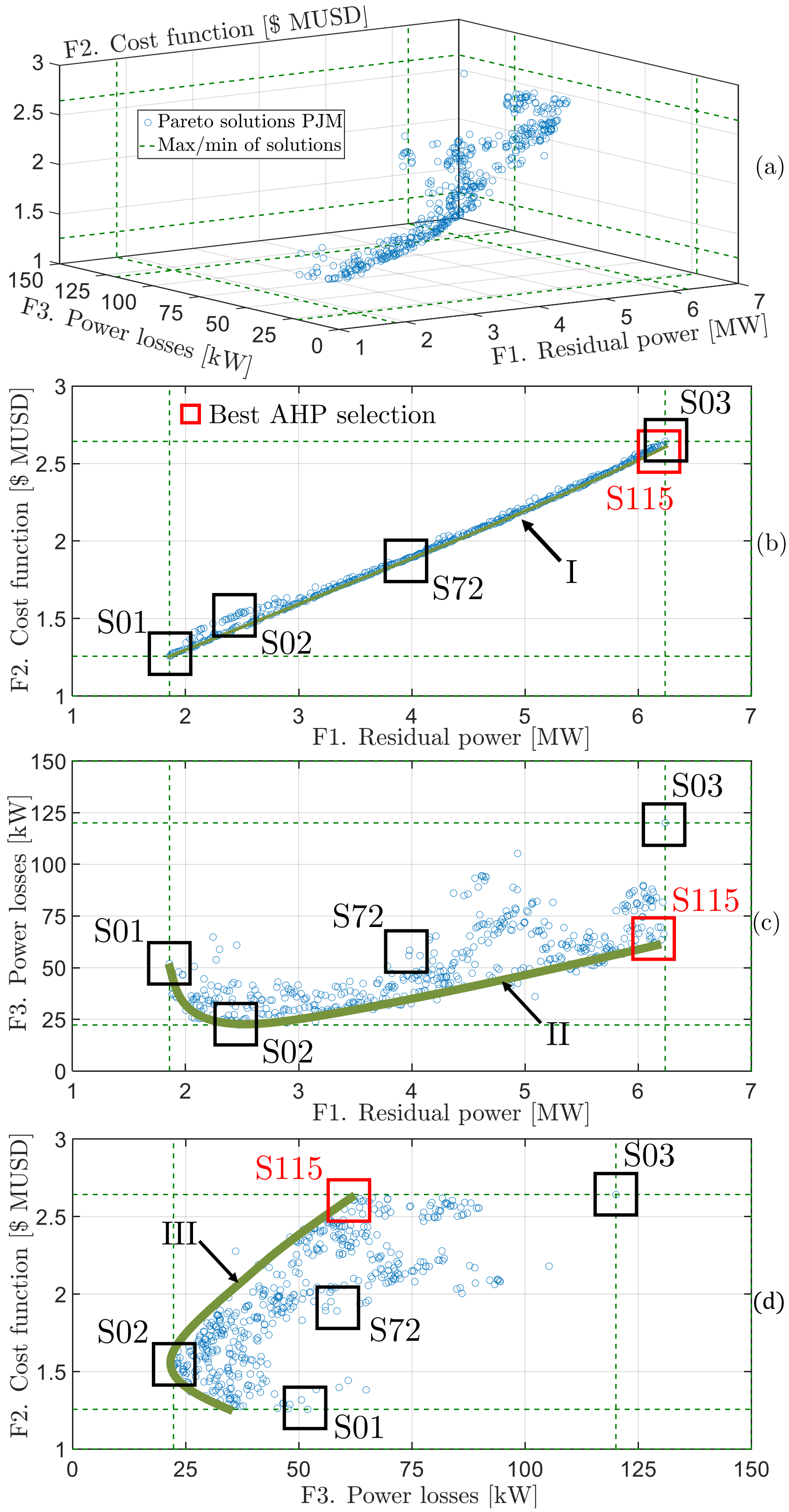

Figure 6-18.: Optimal Pareto solutions for the planning with POMMP in the CS1 under PJM market

Table 6-6.: AHP first selection from the optimal solutions for the Microgrid planning in the CS1 under PJM market

Objective function	Units	Solutions								
		S55	**S63**	**S115**	**S171**	**S186**	**S273**	**S307**	**S363**	**S418**
$F_1(\vec{x})$	[MW]	6,1453	5,9411	6,1022	6,2069	6,1053	6,1205	5,9679	6,1409	5,9767
$F_2(\vec{x})$	[$MUSD]	2,6062	2,5316	2,6160	2,5970	2,5984	2,6031	2,5485	2,6059	2,5603
$F_3(\vec{x})$	[kW]	62,0	61,7	63,5	65,5	63,8	64,3	60,1	62,3	63,4

As a consequence, the AHP procedure is repeated for the nine solutions in Table 6-6 as described in Chapter 4. As a result, the solution **S115** presented the highest ranking R_p.
The best solutions from AHP is compared with the maximum and minimum points of the Pareto optimal set in Table 6-7. Additionally, the solution with the worst ranking in the AHP selection is included in the comparison to analyze the behavior of the AHP technique. The points have been marked in Figure 6-18.

Table 6-7.: Comparative selection from the optimal solutions for the microgrid planning in the CS1 under PJM market

Objective function	Units	Solutions				
		Best AHP	**Worst AHP**	**Max F1-F2**	**Min F1-F2**	**Min F3**
		S115	**S72**	**S03**	**S01**	**S02**
$F_1(\vec{x})$	[MW]	6,2069	3,9805	6,2394	1,8583	2,4690
$F_2(\vec{x})$	[$MUSD]	2,6160	1,8916	2,6427	1,2567	1,5346
$F_3(\vec{x})$	[kW]	63,5	58,4	120,1	51,9	22,3

First, it can be analyzed by comparing the solutions S03 and S01 with the maximum and minimum values for the objective functions F1 and F2, respectively, that an increase of 4,38MW in the available residual power leads to an increase of 0.6349 $MUSD in the operation of the microgrid (Table 6-7). Second, it can be seen in the outcome of the POMMP methodology, that the minimum power losses can be achieved for the solution **S02**, which is 57% smaller than the power losses for the solution **S01** with minimum residual power. Therefore, with the solution **S02**, residual power can be improved in 32.8% regarding **S01** and a cost increase of 22%.
With the multi-objective approach, it is possible *a posteriori* to find a convenient trade-off among the objective functions, with an improvement in the reserve capacity for the AS supplying up to 6,12 MW with the solution **S03**.
Finally, it is possible to have a better understanding of the AHP performance with the location of the solution **S72** in the objective space, Figure 6-18 (d), and values in Table

6-7. It can be seen that the solution is located far from all the maximum and minimum boundaries of the Pareto solutions set. This can be interpreted as the worst trade-off among the three objective functions when the preference order is F1, F2 and F3, respectively. Operational characteristics and PJM electricity market participation capabilities, such as the total energy exported, imported, generated, demanded, revenue and expense purchases, are shown in Table 6-8 for the representative solutions **S115**, **S03**, **S01** and **S02**.

Table 6-8.: Operation characteristics and market revenues for selected comparative solutions in the CS1 under PJM market

Characteristic	**Units**	**Solutions**			
		Best AHP S115	**Max F1-F2 S03**	**Min F1-F2 S01**	**Min F3 S02**
Total energy generated	[GWh/year]	75,3	76,0	37,6	42,4
Total energy demanded	[GWh/year]	28,3	28,3	21,0	20,7
Total energy exported	[GWh/year]	46,4	46,7	16,2	21,5
Total lost energy	[GWh/year]	0,56	1,05	0,45	0,20
Total available residual energy	[GWh/year]	54,2	54,5	16,2	21,6
Revenue from exported energy	[$MUSD]	0,3147	0,3167	0,1052	0,148
Revenue from AS provision	[$MUSD]	0,062	0,062	0,021	0,029

To interpretate the results in Table 6-8, it is important to highlight three characteristics of the microgrid planning:

- The total generated energy considers the possible hourly power generated by the dispatchable and non-dispatchable DGs.
- The microgrid's load demand is influenced by the presence of ESS. Therefore, since they operate as both load or source in the microgrid, total demanded energy is affected by the size and simulated operation of the BAs. This justifies the variations in the total demanded energy among solutions even for the same base test system.
- Contrary to the total generated energy, the total exported energy considers both the DGs' generated power and the hourly delivered and exported power by the BAs in the microgrid. The hourly average available residual power considers the exported power and the stored energy capacity of the BA that can be delivered.

Therefore, results show that despite generated, demanded and exported energies are relatively similar for the analyzed extreme solutions in terms of GWh/year, some relevant variations can be seen. For example, a slight improvement can be found with solution **S115**

regarding **S03**, since the exported energy for **S115** and **S03** are similar with around 61,5% of the total generated energy, the total available residual energy is 1,0% higher concerning the total generated energy for the optimal solution **S115**. Furthermore, although the total demanded energy of solutions **S01** is only 1,0% higher than **S02**, solution **S01** can deliver up to 43,13% of the total generated energy, while solution **S02** can provide up to 50,6% with an increment on the operation cost of 22% in relation with **S01** (Table 6-7). This last fact is a consequence of the reduction on power losses with solution **S02**. Therefore, it can be claimed that the POMMP can offer a set of possible solutions with small technical variations that can give rise to optimal extra savings in the Microgrid operation.
Readers can notice the variation in the relation of the total energy exported and total available residual energy between solutions **S115-S03** and **S01-S02**. This effect is due to the available storage capacity resources that have been optimally selected for the solutions. Therefore, solutions **S115** and **S03** have higher ESS installed capacity than solutions **S01** and **S02**. This is also seen in the increase on the total energy demanded in 36% between solutions **S115** and **S02**. The results of these two last solutions, **S115** and **S02**, are analyzed more in detail below.

Microgrid design for the solution S115

The decision variables for the solution **S115** are summarized in Table 6-9. The microgrid planning for the solution **S115** is shown in the line diagram for the test system in Figure 6-19. Under this planning configuration, the total net installed capacity is equal to 17MW, which would represent maximum energy generated in a year of 148,9 GWh/year. However, results in Table 6-8 show that the total energy generated is 81,5 GWh/year, 54% for the installed capacity.
Numerical results for solution **S115** show also a higher capacity in the wind generation resources, which might be a direct consequence of the used historical data for the wind speed in the Kiel region (North-coast) in Germany. Another possible geographical effect is seen regarding the resulting relatively lower capacity in the solar generation resources. The result might be a consequence of the power solar density in this part of the globe, which is not the most appropriate for PV-based generation matrices.

Microgrid design for the solution S02

The decision variables for the solution **S02** are summarized in Table 6-10, while the microgrid planning for the solution S02 is shown in the line diagram for the test system in Figure 6-20.
It is interesting to analyze the outcomes from solutions **S115** and **S02**. Clearly, capacities for the solution **S02** are lower then the one for the solution **S115**, with a particular difference in the storage energy capacity with the BA. However, locations of WT and PV in the microgrid were shared between both solutions, which lead to an idea of the convenient buses

Table 6-9.: Microgrid design decision variables solution S115 in the CS1 under PJM market

DER Technology	Decision variables solution						TOTAL [kW]
MT	**Rated capacity [kW]**	700	700	665	700	665	3430
	Bus location	39	38	37	14	9	–
WT	**Rated capacity [kW]**	2400	2400	2400	1320	2280	10800
	Bus location	3	5	63	61	52	–
PV	**Rated capacity [kW]**	179	162	160	18	78	596,1
	Bus location	65	11	44	54	27	–
	Rated capacity [kW]	0	119	127	41	123	409,4
	Bus location	56	10	69	32	26	–
BA	**Rated capacity [kW]**	216	0	373	475	701	1764,7
	Bus location	6	33	2	64	29	–
						TOTAL [kW]	17000

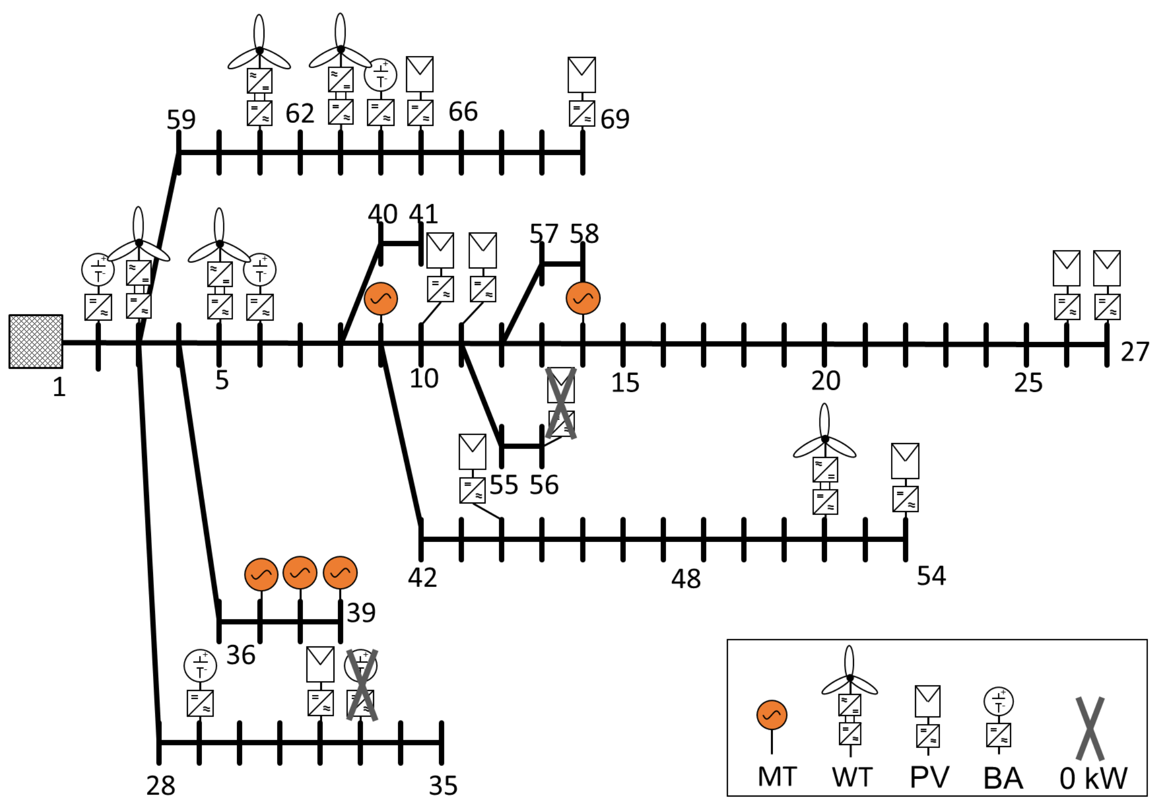

Figure 6-19.: Microgrid planning for solution S115 in the CS1 under PJM market

Table 6-10.: Microgrid design decision variables solution S02 in the CS1 under PJM market

DER Technology	Decision variables solution						TOTAL [kW]
MT	**Rated capacity [kW]**	595	385	385	525	525	2415
	Bus location	53	47	42	2	16	–
WT	**Rated capacity [kW]**	1200	1800	1680	720	960	6360
	Bus location	39	3	60	62	52	–
PV	**Rated capacity [kW]**	189	140	154	2	74	558,3
	Bus location	68	6	29	46	27	–
	Rated capacity [kW]	85	136	113	6	105	444,9
	Bus location	38	8	54	36	41	–
BA	**Rated capacity [kW]**	0	0	22	0	13	35,3
	Bus location	17	40	4	64	30	–
						TOTAL [kW]	9813

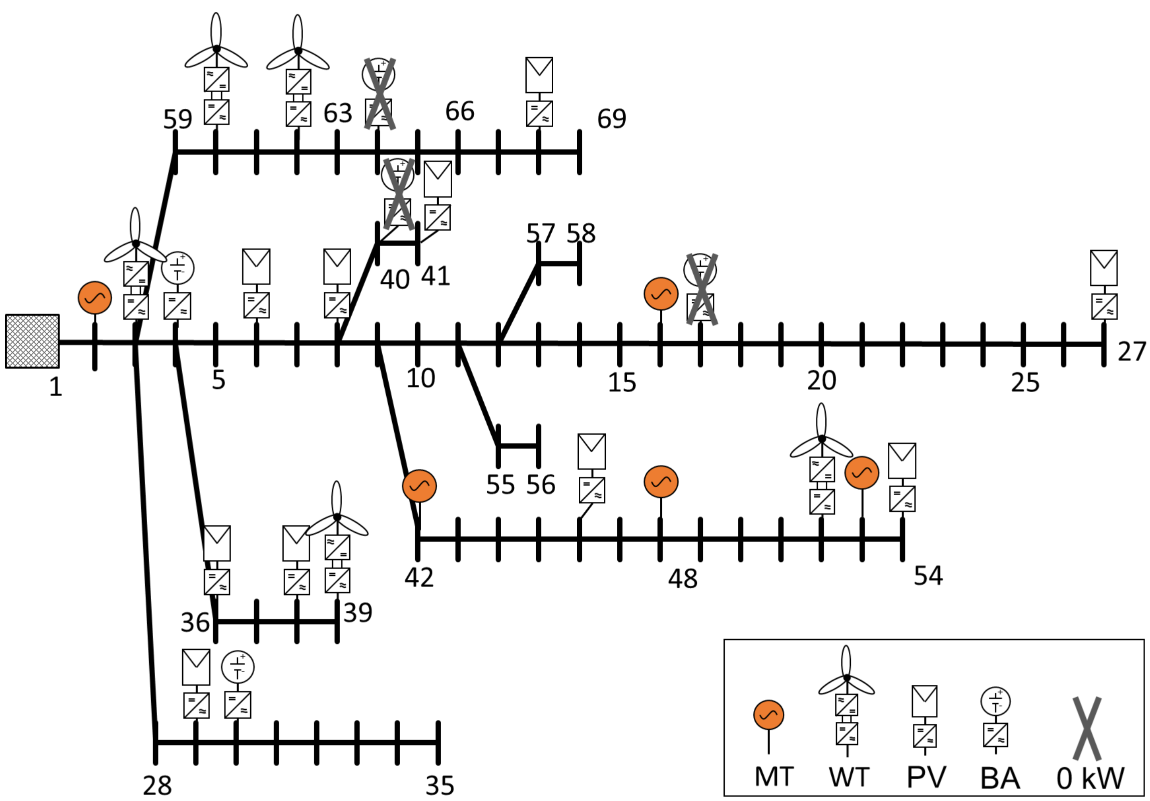

Figure 6-20.: Microgrid planning for solution S02 in the CS1 under PJM market

for generation in the grid. It is important to highlight that the total installed capacity of the solution **S115** is 1,73 times the installed capacity of **S02**. The installed capacity in **S02** would represent 85,96 GWh/year, of which 49,4% is the total energy generation in the solution, Table 6-8. Therefore, it is possible to claim that for the CS1, around 50% of the installed capacity is not effective due to the wind speed and solar irradiance potential independently of the maximum residual power and power losses.

The ratio between non-dispatchable to dispatchable DGs's technologies is 3,04kW to 1kw of installed power for solution **S02**, while this is 3,44kW to 1kW of installed power for solution **S115**. This shows that the ratio of capacities is relatively similar between both solutions, although solution **S115**, with a higher capacity, showed a higher renewable installed capacity.

To conclude, results show the high potential of *a posteriori* analysis in the solution of a planning problem. Different alternatives can be analyzed and found in terms of the decision variables solution. The next step is to study the behavior of the planning methodology for the same case study but different market conditions.

6.4.3. Scenario 2: numerical results for the CAISO market with POMMP methodology

The same conditions and parameter configuration used for the planning under the PJM market characteristics are used to reach numerical results with the CAISO market. The results for the CAISO market are shown in Figure 6-21. Lines I, II and III highlight the convergence boundary for each of the objective functions.

Results in Figure 6-21 show that solutions converge to similar objective functions space area, which is logical because the same base network and parameters, except for the economical factors, are maintained equally. However, *a posteriori* analysis allows us to identify important variations in the maximum and minimum values of the objective functions. The extreme objective function values are highlighted in Figure 6-21 together with the results from the AHP.

Accordingly, eight solutions share the highest-ranking R_p in the first iteration of the AHP. The solutions are shown in Table 6-11.

Table 6-11.: AHP first selection from the optimal solutions for the Microgrid planning in the CS1 under CAISO market

Objective function	Units	Solutions							
		S28	S110	S238	S422	S463	S474	S489	S496
$F_1(\vec{x})$	$[MW]$	9,9056	9,8192	9,9717	9,8229	9,8451	9,9701	9,8406	9,9607
$F_2(\vec{x})$	$[\$MUSD]$	3,1986	3,2071	3,2216	3,1820	3,1984	3,2199	3,1773	3,2182
$F_3(\vec{x})$	$[kW]$	56,8	54,8	57,1	56,9	60,7	57,1	57,0	57,0

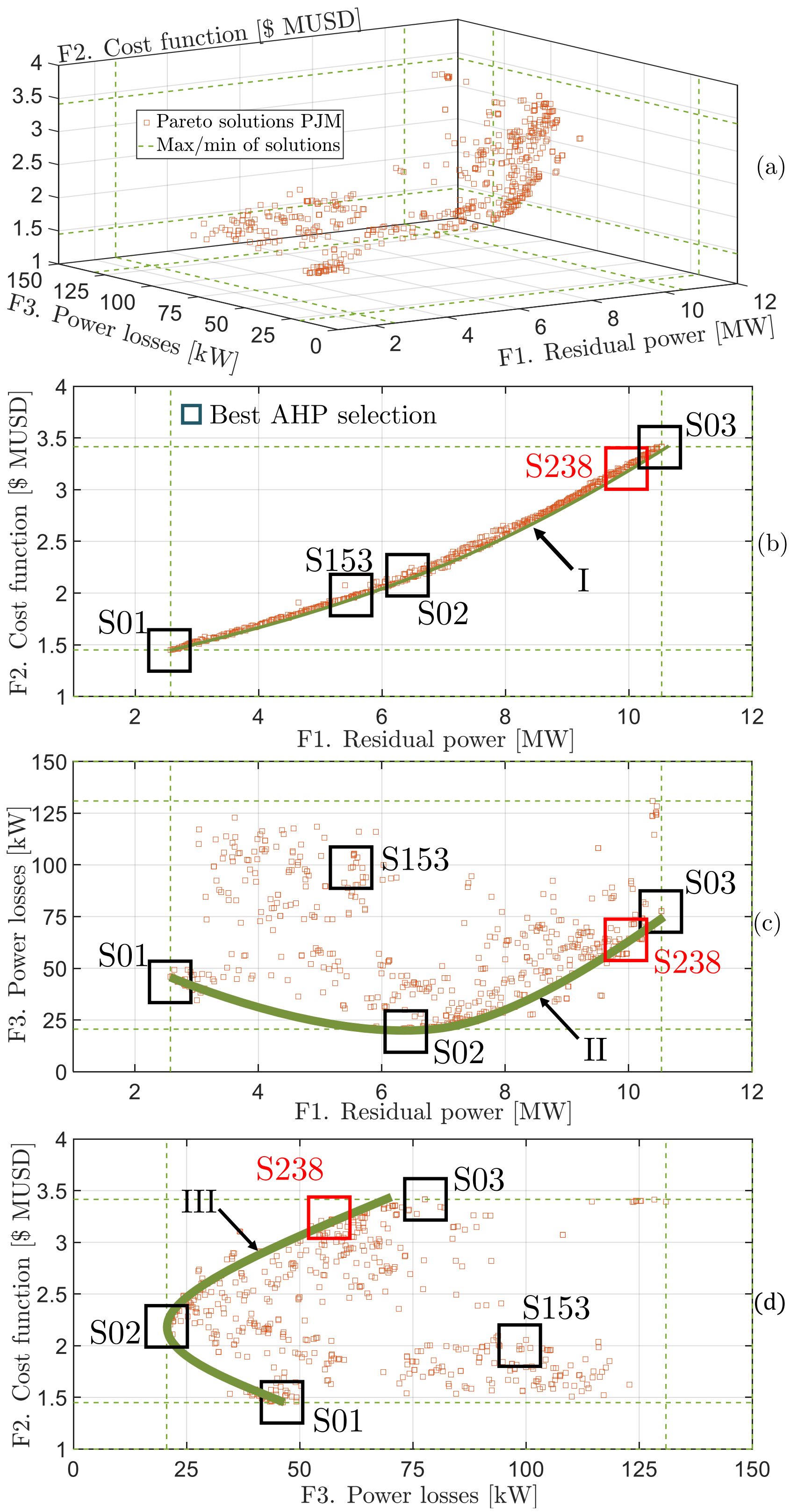

Figure 6-21.: Optimal Pareto solutions for the planning with POMMP in the CS1 under CAISO market

Following the AHP procedure described in Chapter 4, the AHP is repeated with the eight alternatives, where the solution **S238** gave rise to the highest ranking R_p.
The best solutions from AHP is compared with the maximum and minimum points of the Pareto optimal set in Table **6-12**. Additionally, the solution with the worst ranking in the AHP selection (solution **S153**) is once more included in the comparison to analyze the behavior of the AHP technique. The points have been marked in Figure **6-21**.

Table 6-12.: Comparative selection from the optimal solutions for the microgrid planning in the CS1 under CAISO market

Objective function	Units	Solutions				
		Best AHP S238	Worst AHP S153	Max F1-F2 S03	Min F1-F2 S01	Min F3 S02
$F_1(\vec{x})$	[MW]	9,9701	5,5310	10,5317	2,5746	6,4447
$F_2(\vec{x})$	[$MUSD]	3,2199	1,9677	3,4156	1,4497	2,1976
$F_3(\vec{x})$	[kW]	57,1	99,0	77,7	45,9	20,6

Results in Table **6-12** show that the CS1 microgrid can be planned based on the POMMP methodology for the CAISO market with an optimal hourly average available residual power between 2,57MW and 10,53MW and a difference in the operation cost of 1,97$MUSD. Furthermore, it is ratified the effect of the power losses regarding DERs penetration level in the microgrids planning for the CS1. Accordingly, the solution **S02** has the minimum power losses with an average hourly value of 20,6kW, which, for instance, represents savings on 26,5% on the undesirable power losses compared with solution **S03**. Furthermore, the possible hourly average residual power for solution **S02** is 6,44MW, which is 61% of the value for the solution **S03**. Hence, with the multi-objective approach, it is possible to find *a posteriori* a convenient trade-off among the objective functions considering market conditions, which gives the option of analyzing different alternatives as it was done in this case with solution **S02**.
As with the former analysis with the PJM market in the scenario 1, the solution **S153** with the worst ranking of the AHP was located far from the boundaries of the solutions, as it can be seen in Figure **6-21** (d). These can be also visualized with the values of the solution in Table **6-12**, which represent the worst trade-off among the three objective functions.
A wider view of the results can be achieved with the operational characteristics and market participation capabilities for the solutions **S238**, **S03**, **S01** and **S02**. These characteristics are shown in Table **6-13**.
One of the main results of the CS1 for the CAISO market is the one regarding the AS revenue. It is found that there is no revenue for the possible supply of AS to the main grid for optimal solutions. This is because the AS clearing price for the CAISO market is on average 6,27 times lower compared with the PJM market, and it is lower than the wholesale market clearing

Table 6-13.: Operation characteristics and market revenues for selected comparative solutions in the CS1 under CAISO market

Characteristic	Units	Solutions			
		Best AHP S238	**Max F1-F2 S03**	**Min F1-F2 S01**	**Min F3 S02**
Total energy generated	[GWh/year]	63,0	67,9	37,6	39,6
Total energy demanded	[GWh/year]	20,6	20,6	20,6	20,6
Total energy exported	[GWh/year]	41,9	46,7	16,6	18,9
Total lost energy	[GWh/year]	0,50	0,68	0,40	0,18
Total available residual energy	[GWh/year]	87,1	92,0	22,5	56,3
Revenue from exported energy	[$MUSD]	0,2023	0,226	0,0771	0,0884
Revenue from AS provision	[$MUSD]	0	0	0	0

prices (See Appendix B). Hence, it is more profitable to sell electricity to the wholesale CAISO electricity market. Readers can recall that POMMP methodology is formulated for maximizing the residual power for being exported to the main grid based on the clearing prices and the maximization of the microgrid's profit (minimization of the operation cost). Therefore, POMMP methodology can be adapted to different market conditions, for example, a microgrid with dedicated participation for AS provision.

Additional results for the CS1 planning with POMMP for the CAISO market are in the charging/discharging cycles of the installed batteries. Recalling the batteries simulation strategy proposed in Chapter 3, batteries, or ESS in general, are active elements in the microgrid with a relevant level of flexibility in their operation and functionality. Therefore, the operation strategy for POMMP is defined according to the SOC, time of the day, and binary variables for the AS demand (See Chapter 3). Consequently, due to the market conditions, BAs operate mainly based on the daily charging and discharging strategy based on the microgrid's and wholesale market demand. Hence, BAs planning capacity is found similar independently of the DGs capacity. This can be observed in the total energy demanded, since the BAs' charging demand is similar in all solutions.

It is also visible that the total available residual energy is on average 38% higher than the total energy generated. This percentage is due to the average daily storage energy in the BA systems that are not delivered. However, relevant differences regarding power losses among solutions are also found. For example, the total lost energy is reduced in 63,9% between solutions **S238** and **S02**, the total energy generated is reduced in 58,9% and the total residual energy is reduced in 35,35%, which might represent advantages in the performance of the microgrid. An overview of these two solutions is given below.

Microgrid design for the solution S238

The decision variables for the solution **S238** are summarized in Table 6-14. The microgrid planning for the solution **S238** is shown in the line diagram for the test system in Figure 6-22.

Under this planning configuration, the total net installed capacity is equal to 18,9MW, which would represent maximum energy generated in a year of 165,5 GWh/year. However, results in Table 6-13 show that the total energy generated is 63,0 GWh/year, 38,06% of the installed capacity.

The solution **S238** shows also the high capacity in the energy storage resources and the same tendency regarding wind generation and solar generation capacities than solutions for the PJM scenario.

Table 6-14.: Microgrid design decision variables solution S238 for CS1 under CAISO market

DER Technology	Decision variables solution						TOTAL [kW]
MT	**Rated capacity [kW]**	595	700	700	700	700	3395
	Bus location	2	40	28	56	47	–
WT	**Rated capacity [kW]**	1680	2280	2040	2280	1560	9840
	Bus location	29	63	3	5	52	–
PV	**Rated capacity [kW]**	172	109	0	20	68	368,3
	Bus location	64	15	30	46	61	–
	Rated capacity [kW]	159	7	152	8	36	362,8
	Bus location	27	16	38	26	21	–
BA	**Rated capacity [kW]**	1200	1190	1200	144	1199	4933,5
	Bus location	17	53	41	32	23	–
						TOTAL [kW]	18900

Microgrid design for the solution S02

The decision variables for the solution **S02** are summarized in Table 6-15. The microgrid planning outcome for the solution S02 is shown in the line diagram for the test system in Figure 6-23.

Results for the solution **S02** confirm the influence of the market on the capacity of the BA systems, which represent 31,8% of the total installed capacity for the solution S02 (26,1% for solution S238). The installed capacity in **S02** would represent total energy of 112,5 GWh/year, while the actual total energy generation is 35,4% of the total energy generation.

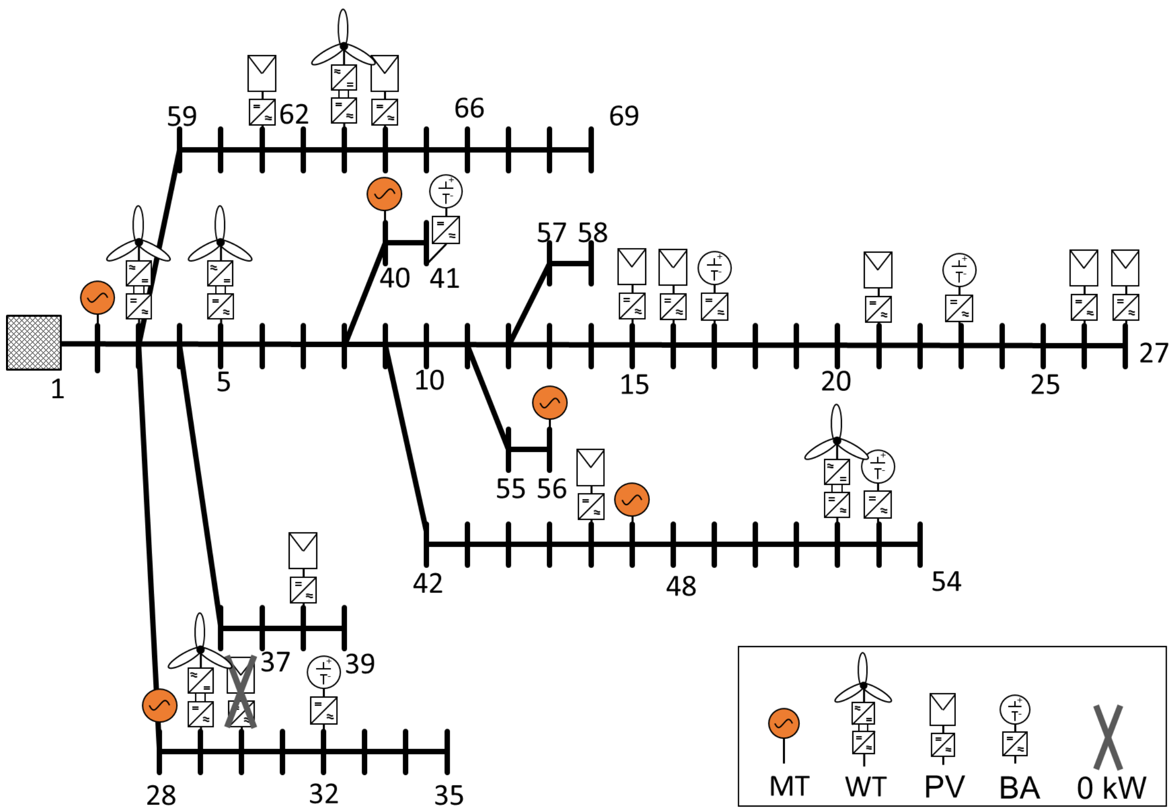

Figure 6-22.: Microgrid planning for solution S238 for the CS1 under CAISO market

This behavior gives rise to analyze the role of the ESS in the POMMP methodology. One of the objective function of the methodology is the maximization of the residual power to provide AS or export power to the main grid. For that purpose, the BA systems can operate changing their charging/discharging cycle depending on binary variables for the provision of the services (See Chapter 3). In the CAISO market, the clearing prices for the AS capacity are lower than the prices for selling energy to the wholesale market. Therefore, residual power is mainly exported to the stock market and BA systems maintained charged in case AS are required. As a consequence, the capacity of the BAs are closer to the upper boundary limits.

For the **S02**, the ratio between non-dispatchable to dispatchable DGs's technologies is 1,94kW to 1kW of installed power for solution **S02**, while this is 3,11kW to 1kW of installed power for solution **S238**. This shows a representative difference in the ratio of capacities between both solutions, with solution **S238** having a higher capacity represented on a higher renewable installed capacity.

These results show the relevance of an *a posteriori* analysis, which can be better visualized comparing the representative solutions **S115**-PJM and **S02**-PJM for the PJM market and **S238**-CAISO and **S02**-CAISO for the CAISO market.

Table 6-15.: Microgrid design decision variables solution S02 for the CS1 under CAISO market

DER Technology	Decision variables solution						TOTAL [kW]
MT	**Rated capacity [kW]**	560	700	420	595	700	2975
	Bus location	53	39	20	42	52	–
WT	**Rated capacity [kW]**	1080	840	1920	720	600	5160
	Bus location	29	63	60	4	48	–
PV	**Rated capacity [kW]**	129	48	2	20	94	293,1
	Bus location	64	6	43	47	40	–
	Rated capacity [kW]	154	9	139	5	21	328,5
	Bus location	25	23	46	33	21	–
BA	**Rated capacity [kW]**	1157	983	611	138	1200	4088
	Bus location	26	65	54	34	22	–
						TOTAL [kW]	12845

6.4.4. Comparative analysis of the results for the PJM and CAISO markets with POMMP methodology

To have an overall overview of the planning solutions for the CS1 in both market scenarios, PJM and CAISO, the Pareto optimal set solutions are shown in Figure 6-24. Lines I, II and III highlight the convergence boundary for each of the objective functions and the markets. Results in Figure 6-24 show the influence of the market-clearing prices for the POMMP methodology. The effect of the market leads to clear variations in the values of the possible available residual power. For example, the maximum value of the residual power for the PJM scenario with the solution **S03** (Table 6-7) is 6,23MW, while the result for the CAISO market conditions is 10,53MW (Table 6-12). Nonetheless, the average maximum hourly power losses in the Pareto optimal set are close with 120,1kW for PJM and 130,9kW for CAISO.

A similar result can be seen with the minimum value of the average daily power losses. The minimum value for the solution **S02** for the two markets is 22,29kW for PJM and 20,58kW for CAISO (7,6% smaller). Therefore, the total lost energy for the two solutions is 0,20GWh/year for PJM and 0,18GWh/year for CAISO. Furthermore, the total demanded energy is 20,7GWh/year and 20,6GWh/year, respectively.

However, the average daily available residual power capacity for the CAISO scenario (6,4447MW) is 61,6% higher than the value for the solution under the PJM market condition (2,4690MW) and represent a total available residual energy of 56,3GWh/year and 21,6GWh/year respectively. However, the total energy generated with the solution **S02** under the CAISO condi-

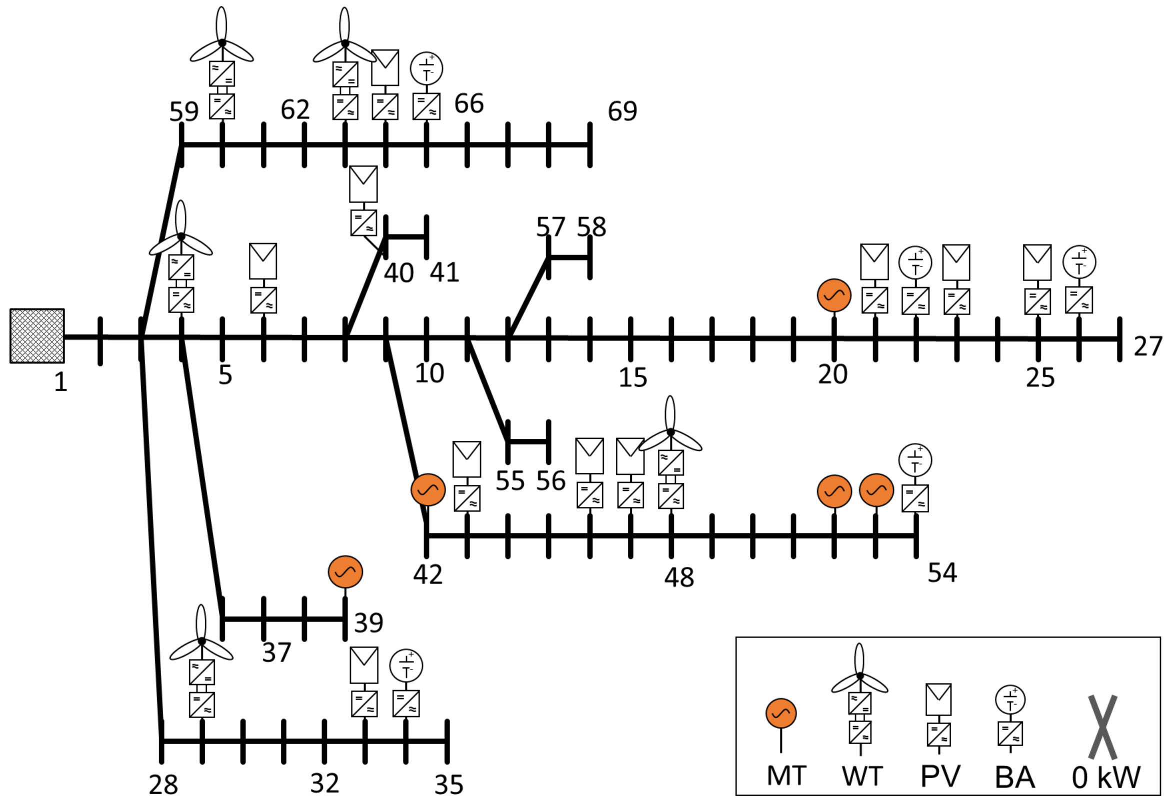

Figure 6-23.: Microgrid planning for solution S02 for the CS1 under CAISO market

tions is 39,6GWh/year, while under the PJM conditions it is 42,4GWh/year (6,6% higher). Furthermore, the final generation installed capacity is 8,75MW (68,17% of the total installed DER's capacity) for the solution **S02** under the CAISO scenario and 9.77MW (99,64% of the total installed DER's capacity) for the solution **S02** under the PJM scenario. Consequently, the results make evident the impact of the market conditions on the energy storage resource size. This outcome is mainly due to the generation flexibility that the energy storage resources can introduce in the power delivery and AS provision by the microgrid.

6.4.5. Numerical results for the PJM market with POMMP methodology and MOEA/D

As part of the research presented here, different true-multi-objective population-based metaheuristic optimization algorithms were tested to evaluate the algorithm's performance of the optimization for solving the microgrid planning problem. One of the tested algorithms was the MOEA/D, which was described in Chapter 4.

With the parameters tuned by Lopez Rivera and Rodríguez Bejarano (2019), the MOEA/D algorithm was used in the POMMP methodology to solve the optimization problem for the CS1 under the PJM market conditions. The "Limit 5" of the decision variables is adopted, as

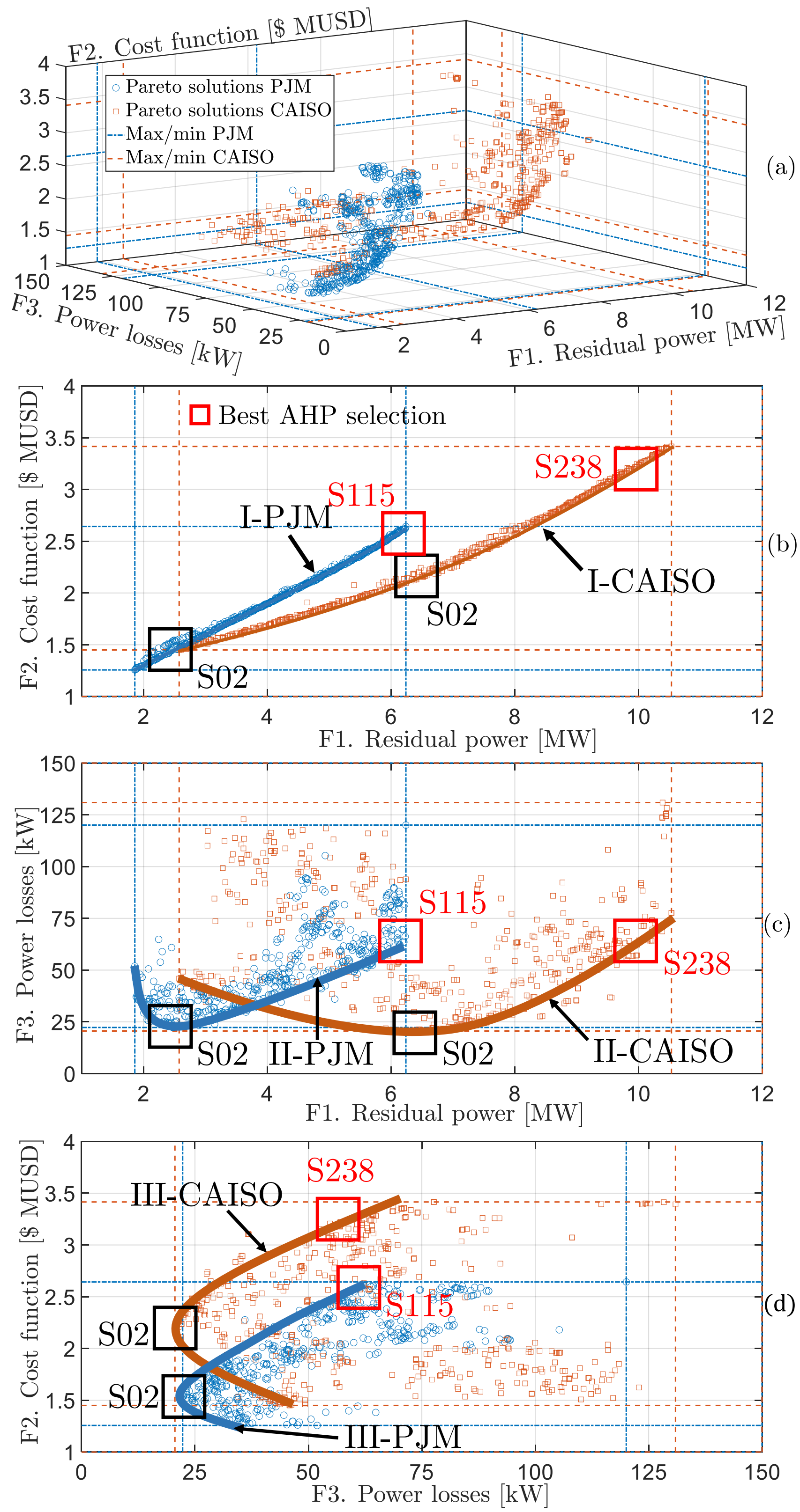

Figure 6-24.: Comparison of the optimal Pareto solutions for the planning with POMMP and PJM and CAISO markets

well as model, climate and market parameters used in the former results. Numerical results are compared with the solution with the NSGAII algorithm presented in Figure **6-18**. The optimal Pareto solutions set for the two algorithms are presented in Figure **6-25**.
The optimal Pareto solutions for the two optimization algorithms show a different performance. It can be seen that the maximum and minimum values for the objective functions of residual power F1 and microgrid's cost F2 are relatively similar. However, the convergence of the solutions in terms of the power losses is more deficient for the solution with the MOEA/D algorithm. The maximum and minimum value limits for the two solution sets are summarized in Table **6-16**.

Table 6-16.: Characteristic values for the NSGAII and MOEA/D Pareto solutions

Objective function	**Units**	**Optimization algorithm**		**Difference**
		NSGAII	**MOEA/D**	
Maximum value F1 residual power	$[kW]$	6,24	5,12	1,12
Minimum value F1 residual power		1,86	1,06	0,80
Maximum value F2 cost function	$[\$MUSD]$	2,64	2,63	0,01
Minimum value F2 cost function		1,26	1,36	0,11
Maximum value F3 power losses	$[kW]$	0,13	2,15	2,02
Minimum value F3 power losses		0,02	0,07	0,05
Hypervolume	–	0,2832	5,5046	5,22

Conversely, the hypervolume indicator for the solutions show a substantial difference, giving a value of 0,2832 for NSGAII, and 5,50 for MOEA/D. It is also noticed that the NSGAII solutions converge to a region in the objective space bounded by 6,24-1,86MW, 2,64-1,26$MUSD and 0,13-0,02MW for objective function F1, F2 and F3, respectively, while the MOEA/D solutions are bounded by 5,12-1,06MW, 2,63-1,36$MUSD and 2,15-0,07MW for objective function F1, F2 and F3, respectively. For this reason, it is possible to claim that the reached power losses for approximately the same value of available residual power are higher in the solutions with MOEA/D. In former sections of this chapter a similar behavior for the solutions with the algorithm NSGAII but a lower number of function evaluations was found. However, the hypervolume indicator is higher for the MOEA/D algorithm with a value of 5,50, while this is 0,28 for the solutions with NSGAII. It can be said that the coverage and diversity are higher, which might lead to a wider range of possibilities on the solutions with

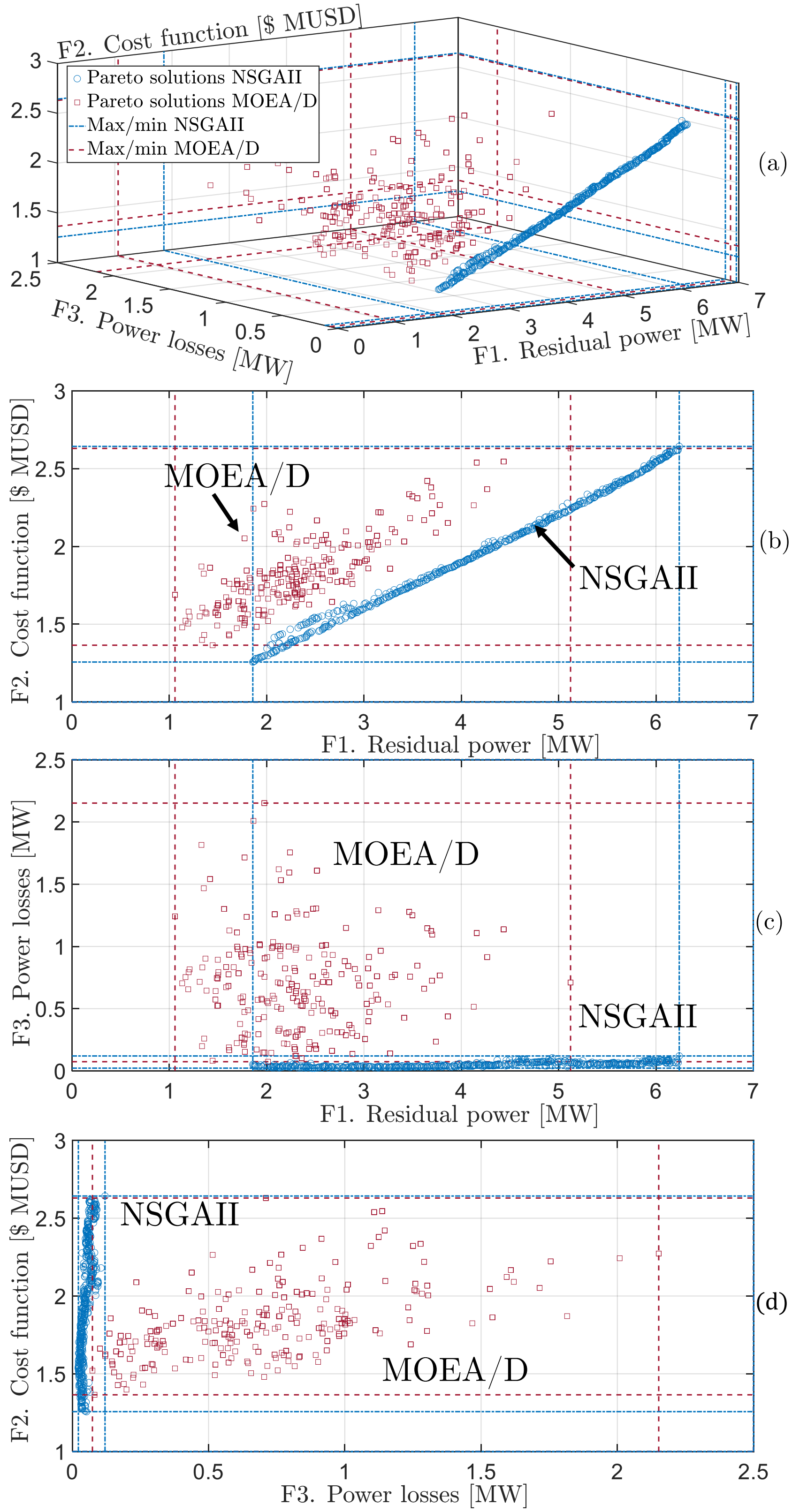

Figure 6-25.: Comparison of the optimal Pareto solutions for the planning solved with NSGAII and MOEA/D

MOEA/D. This can be corroborated with the C-metric, since it is found that none of the solutions sets obtained by MOEA/D and NSGA-II have individually dominated solutions by the other algorithm, respectively.
To sum up, the results would indicate that the set of solutions obtained through MOEA/D can achieve a bigger diversity in the solutions, which is visible with the difference obtained in the hypervolume indicator. Furthermore, it is possible to claim that the difference obtained with the hypervolume indicator is attributed exclusively to the diversity of solutions since in terms of the dominance definition, it is not possible to affirm that individual solutions found with MOEA/D offer better microgrid planning solutions than the one with NSGA-II.

6.5. Case study 2 - (CS2): Microgrid planning for the IEEE 37-bus medium voltage distribution network

The CS2 is formulated based on the IEEE 37-Bus Test feeder base case. The test system is a three-phase radial-based feeder with 4.8kV operating voltage, underground line segments with a so-called configuration 722 between bus 1-5, and 723 for all others, and all loads are spot loads with constant PQ, current and impedance and whose values are the sum of the phase demand of the test system (Kersting, 1991; IEEE PES, 2020). However, the set of connection options and distances are adopted from Cortes, Contreras and Shahidehpour (2018) and Che *et al.* (2017b) as shown in Figure **6-26**.
The base power and voltage of the system are set to be 2,5 MVA and 4,8 kV. The total power for the base case radial configuration is P=1827 kW, and Q=886 kVAr. The load data and PJM market characteristics are included in Appendix A of this dissertation.
Two scenarios are proposed for testing POMMP and POMMP2:

- **Scenario 1:** Networked microgrid planning with two dispatchable units.
- **Scenario 2:** Networked microgrid planning with four dispatchable units.

In both scenarios, a planning horizon of one year with time-steps of one hour and three typical days per month are embraced according to the strategy described before.
A loop-based topology configuration with ($N_{\lambda_{clu}} = 2$) and ($N_{\lambda_{clu}} = 4$), respectively, are adopted for both scenarios. Numerical results of the planning for the CS2 with POMMP2 are compared with simulations of the planning for the same case study but with POMMP. For that purpose, two scenarios are used:

- Planning for the CS2 with POMMP and the preset loop-based topology found in (Cortes, Contreras and Shahidehpour, 2018).
- Planning for the CS2 with POMMP for the the preset radial-based topology in (IEEE PES, 2020).

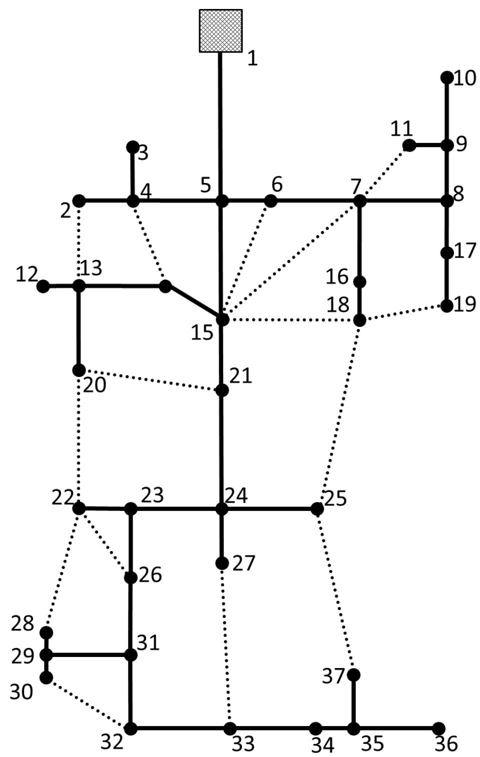

Figure 6-26.: Test system IEEE 37-Bus (not to scale) for the CS2, adapted from Cortes, Contreras and Shahidehpour (2018)

6.5.1. Decision variables limits and particular parameters

The final selection of the decision variables limits was managed according to the recommendations found in Section 6.2. The DER's capacity limits (decision variables limits) are described in Table **6-17**, while all the buses of the network are candidates for the DERs location and all the branches are candidates to define the topology.

The POMMP and POMMP2 methodologies are defined for calculating the uncertainty variables with 5000 iterations in the MCS and to consider the random variability in the multilevel graph partitioning with 1000 iterations.

The optimization problem is tackled with 500 individuals and 100 generations, which were running 10 times for each scenario to confirm the convergence and robustness of the methodology.

Table 6-17.: Standard DG unit sizes and optimization boundaries

DG type / Case	No. Units	Lower boundary P_{lb} [kW]	Upper boundary P_{ub} [kW]
Discrete variables			
MT Case 1	2	5×120	15×120
MT Case 2	4	5×120	15×120
WT	2	0×120	5×120
Continuous variables			
PV	2	0	180
BA	4	0	120

6.5.2. Scenario 1: networked microgrid planning with two dispatchable units

The results of the planning with POMMP2 and POMMP for a radial-based and loop-based reference topologies are shown in Figure **6-27**.
Figure **6-27** shows that POMMP2 can get optimal results (line II) in the same space area than the planning results with POMMP for the reference optimal loop-based topology of Cortes, Contreras and Shahidehpour (2018). Furthermore, the Pareto front outcome shows features for the decision-making on networked microgrid planning. For example, the line I in Figure **6-27**(b) highlight the Pareto solutions from POMMP over the reference radial-based topology, while the line II describe the Pareto front for the planning with POMMP2. It can be seen that the topology planning with a loop-based condition gives rise to solutions with a reduction in power losses. However, an increment was also found in the microgrid cost as it is seen in Figure **6-27**(a).
The solution **S396** from the POMMP2 planning and **S86** from the POMMP over a radial-based topology are chosen with the AHP preferences described in Section 6.3. The values are shown in Table **6-18**. Furthermore, a summary of the location and capacity of the DERs in the networked microgrid is presented in Table **6-19** and the decision variables results are shown in Figure **6-28**.
The results show that POMMP2 places the DERs with a wider distribution than POMMP, highlighting the location of the two MT and the WT in Figure **6-27**. Furthermore, it can be seen that the initial generation portfolio limits with 2 MT units, 2 WT units, 2 PV systems and 4 BA systems was optimally adjusted to 2 MT units, 1 WT unit, 2 PV systems and 4 BA systems in the solution **S396**, and 2 MT units, 1 WT unit, 1 PV system and 3 BA systems in the solution **S86**. Furthermore, the 29.1% and 29.8% of the installed DG's capacity for **S396** and **S86**, respectively, can be delivered as reserve power, while the losses are 0.37% and 0.54%, respectively, that might represent a reduction up to 31MWh energy losses during

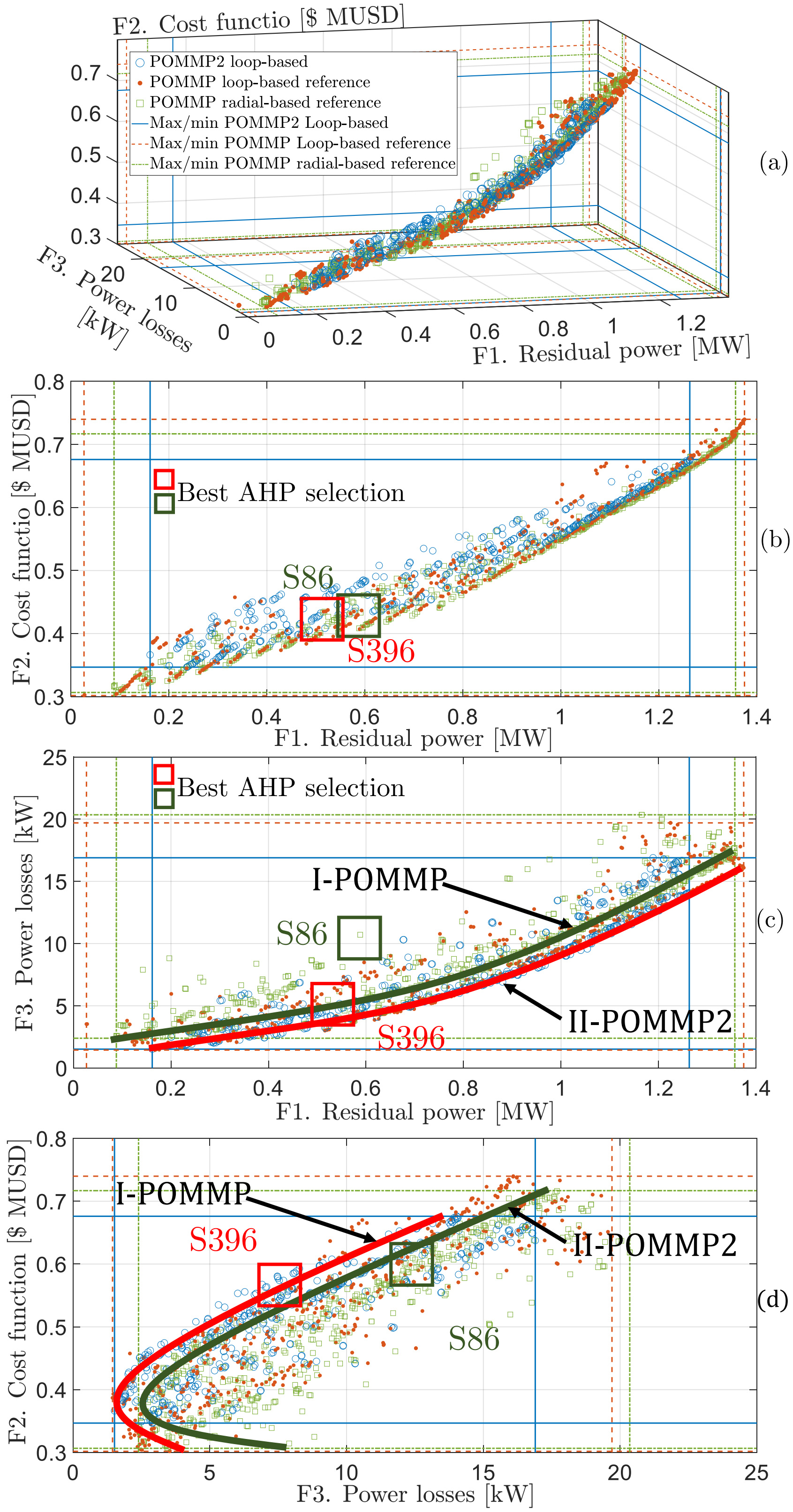

Figure 6-27.: Pareto solutions for two dispatchable units in the CS2, adapted from Contreras *et al.* (2020b)

Table 6-18.: Comparative selection from the optimal solutions for the microgrid planning in CS2, scenario 1

Objective function	Units	Solutions from AHP	
		POMMP2 loop-based S396	**POMMP radial -based S86**
$F_1(\vec{x})$	[MW]	0,56	0,59
$F_2(\vec{x})$	[$MUSD]	0,4324	0,408
$F_3(\vec{x})$	[kW]	7,2	10,7

Table 6-19.: Microgrid design decision variables solutions S396 for POMMP2 loop-based and S86 for POMMP radial-based

DER technology	Variables set	Decision variables solution					
		POMMP2 S396		**TOTAL [kW]**	**POMMP S86**		**TOTAL [kW]**
MT	**Rated capacity [kW]**	875	828	1703	875	973	1848
	Bus location	2	31	–	2	5	–
WT	**Rated capacity [kW]**	0	120	120	0	120	120
	Bus location	12	36	–	13	16	–
PV	**Rated capacity [kW]**	129	48	177	10	0	10
	Bus location	3	29	–	23	14	–
BA	**Rated capacity [kW]**	82	75	157	0,2	19	19
	Bus location	8	14	–	18	24	–
	Rated capacity [kW]	59	60	119	0	0,6	0,6
	Bus location	15	30	–	31	25	–
		TOTAL [kW]		2276	**TOTAL [kW]**		1998

a year; 0.6% of the exported energy from the reserve during the same period.

Hypervolumen and confiability of the results

The hypervolume indicator was used to compare the resulting Pareto fronts from 10 runs. The hypervolume media from the 10 case simulations is $\bar{\text{HV}} = 869$ with a standard deviation of $\sigma = 51.9$ for the case 1, while it is $\bar{\text{HV}} = 836$ with a standard deviation of $\sigma = 74.9$. The Pareto front with the highest hypervolume indicator for each case was chosen for the analysis of the results.

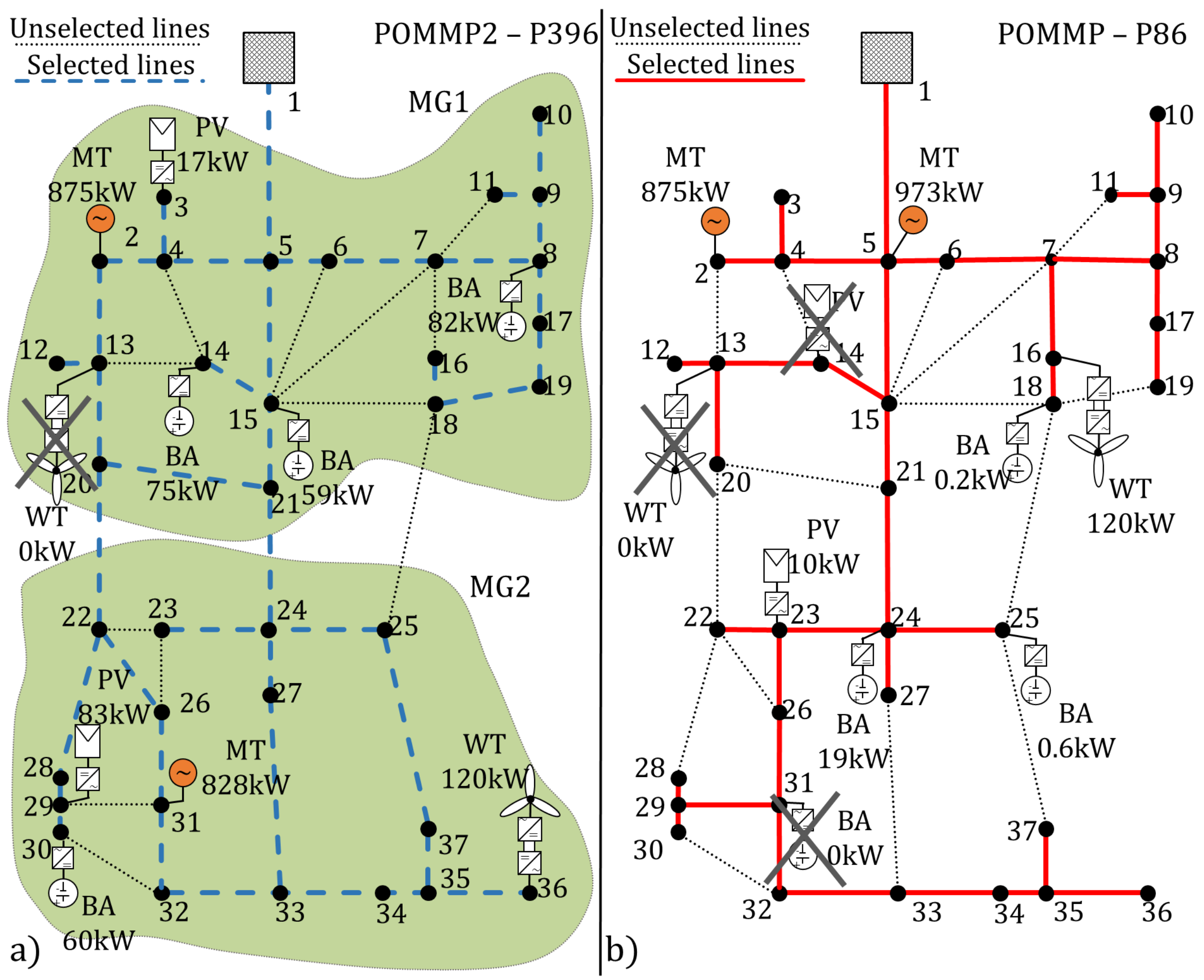

Figure 6-28.: a) Topology based on clusters; b) Radial-based topology, adapted from Contreras *et al.* (2020b)

6.5.3. Scenario 2: networked microgrid planning with four dispatchable units

The results of the planning with POMMP2 and POMMP (for a radial-based and loop-based reference topologies) are shown in Figure **6-29**.

The line II highlights the solutions of POMMP2 and POMMP for the reference loop-based topology. This shows the capacity of POMMP2 to achieve an optimal set of Pareto solutions under the holistic perspective even for a higher number of decision variables and clusters. In this case, the separation in the power losses and cost of the line II with the reference radial-based planning (line I) is wider than in the scenario 1, which can be understood as a consequence of the higher penetration of DERs with the extra two MT units. Furthermore, the residual power capacity to provide AS or participate in open-markets can be almost two

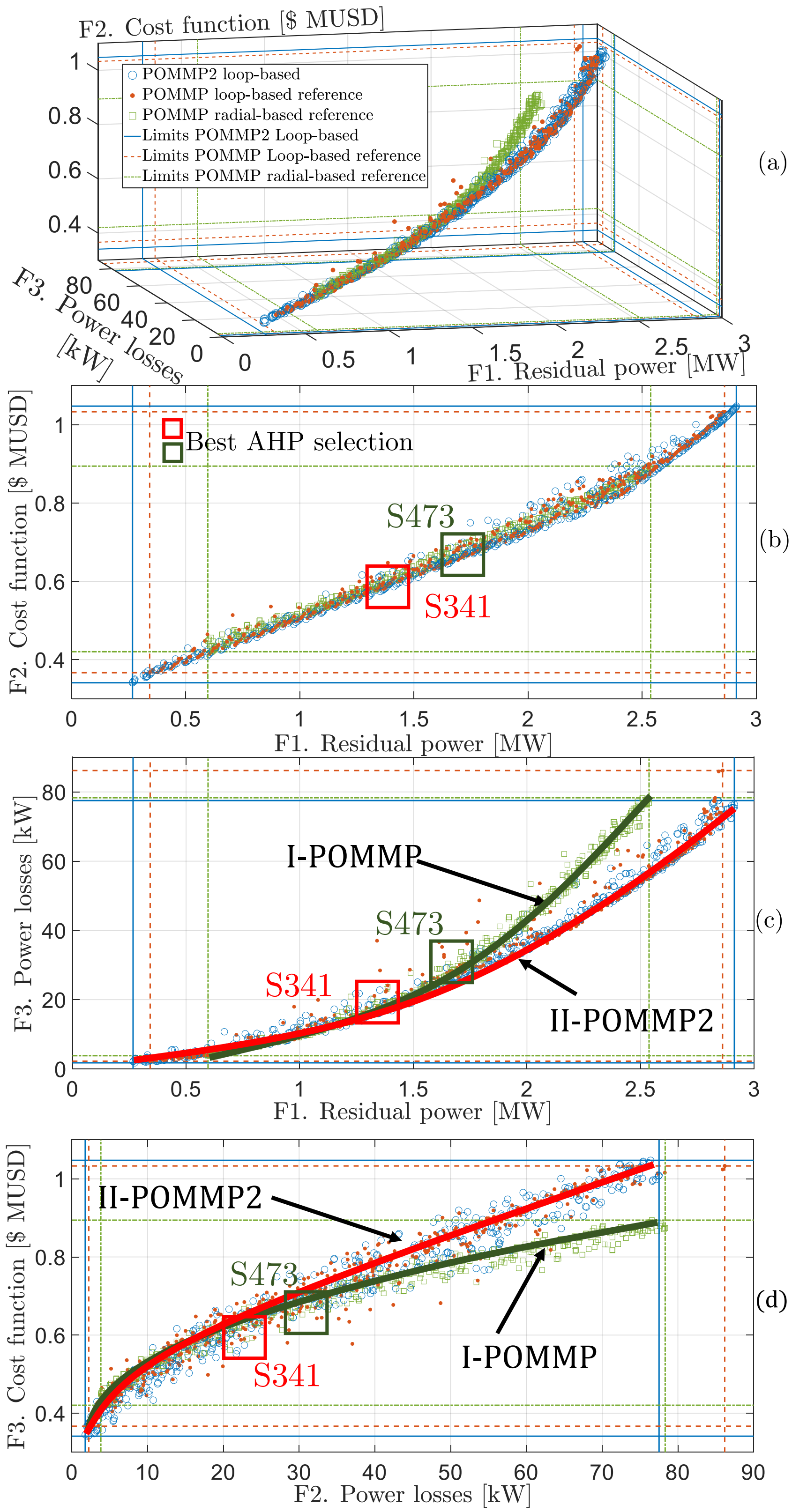

Figure 6-29.: Pareto solution for four dispatchable units, adapted from Contreras *et al.* (2020b)

times higher than in scenario 1 with two MT, which confirms the relevance of *a posteriori* analysis based on a multi-objective methodology.

AHP was used to select two optimal solutions from the Pareto fronts for POMMP2 and POMMP for the radial-based topology. The decision variables results for the solutions **S341** (POMMP2) and **S473** (POMMP) are shown in Figure 6-29. The output objective functions in this case are shown in Table 6-20. Furthermore, the decision variables results are shown in Figure 6-30, and a summary of the location and capacity of the DERs in the networked microgrid are presented in Table 6-21.

Table 6-20.: Comparative selection from the optimal solutions for the microgrid planning in CS2, scenario 2

Objective function	**Units**	**Solutions from AHP**	
		POMMP2 loop-based S341	**POMMP radial -based S473**
$F_1(\vec{x})$	[MW]	1,35	1,65
$F_2(\vec{x})$	[$MUSD]	0,5598	0,673
$F_3(\vec{x})$	[kW]	22,8	31,5

From results, it can be seen that the DERs placement is achieved with greater coverage with POMMP2. A second remark is related to the generation portfolio since it is optimally adjusted to 6 MT units, 0 WT units, 2 PV systems, and 4 BA systems, in the **S341** and 2 MT units, 0 WT units, 1 PV system and 3 BA system in **S473**. Furthermore, it can be mentioned that there is a trend to group the generation units close to the disconnected feeder when the planning of DERs is done without considering topology but contemplating a continuous islanding operation as in the planning with POMMP with radial-based topology. Hence, it can be claimed that the role of the dispatchable units will influence the planning to guarantee reliable operation in islanded mode, which is not visible with traditional planning methodologies. Additionally, results show that the losses in POMMP are 39% higher than the value from POMMP2.

6.6. Final remarks and global analysis of the results

In this chapter, simulation results were presented for the planning of a MV microgrid and a networked microgrid based on the proposed POMMP and POMMP2 planning methodologies. The behavior and performance of the methodologies were analyzed based on a parameter tuning overview and results were compared for two case studies and two planning scenarios, respectively.

The microgrid planning task is a complex engineering problem whose actual solutions cannot

Table 6-21.: Microgrid design decision variables solutions S341 for POMMP2 loop-based and S473 for POMMP radial-based

DER technology	Variables set	Decision variables solution					
		POMMP2 S341		TOTAL [kW]	POMMP S473		TOTAL [kW]
MT	**Rated capacity [kW]**	948	437	1385	656	1021	1677
	Bus location	5	11	–	2	4	–
	Rated capacity [kW]	729	875	1604	948	656	1604
	Bus location	31	33	–	11	24	–
WT	**Rated capacity [kW]**	0	0	0	0	0	0
	Bus location	10	36	–	12	37	–
PV	**Rated capacity [kW]**		26	26	0	20	20
	Bus location	20	22	–	18	19	–
BA	**Rated capacity [kW]**	103	118	221	9,0	25	34
	Bus location	13	8	–	20	21	–
	Rated capacity [kW]	44	55	99	4	0,0	4,0
	Bus location	30	27	–	23	25	–
		TOTAL [kW]		3335	**TOTAL [kW]**		3339

be accurately forecasted *a priori*. For that reason, it is practically impossible to know in advance the final feasible solutions space. Consequently, the potential of a true-multi-objective planning methodology is explored along with the results in the current chapter. For example, maximum and minimum possible values for the available residual power and the trade-off with the microgrid operation cost and power losses are identified with the outcome of the POMMP and POMMP2 methodologies. As a result, final decision-making based on these set of Pareto solutions allows decision-makers (stakeholders) to find final and definitive solutions to the planning problem based on available data, as it could be seen with the results of the CS1 and CS2.

Therefore, it can be claimed that the hypothesis 1 (HS1) for the current research can be confirmed and supported on the results for the CS1 and CS2: A microgrid planning methodology based on a true-multi-objective optimization model is necessary for enhancing the microgrid's benefits and impacts.

Additionally, results for the CS2 show the advantages of the POMMP2 methodology regarding traditional planning approaches with separated planning tasks between power resources and network topology. For example, it was found that the microgrid losses can be reduced with an optimal loop-based topology compared with a radial-based for similar residual power capacity, which was found for the solutions with POMMP2. In short, it can be argued that

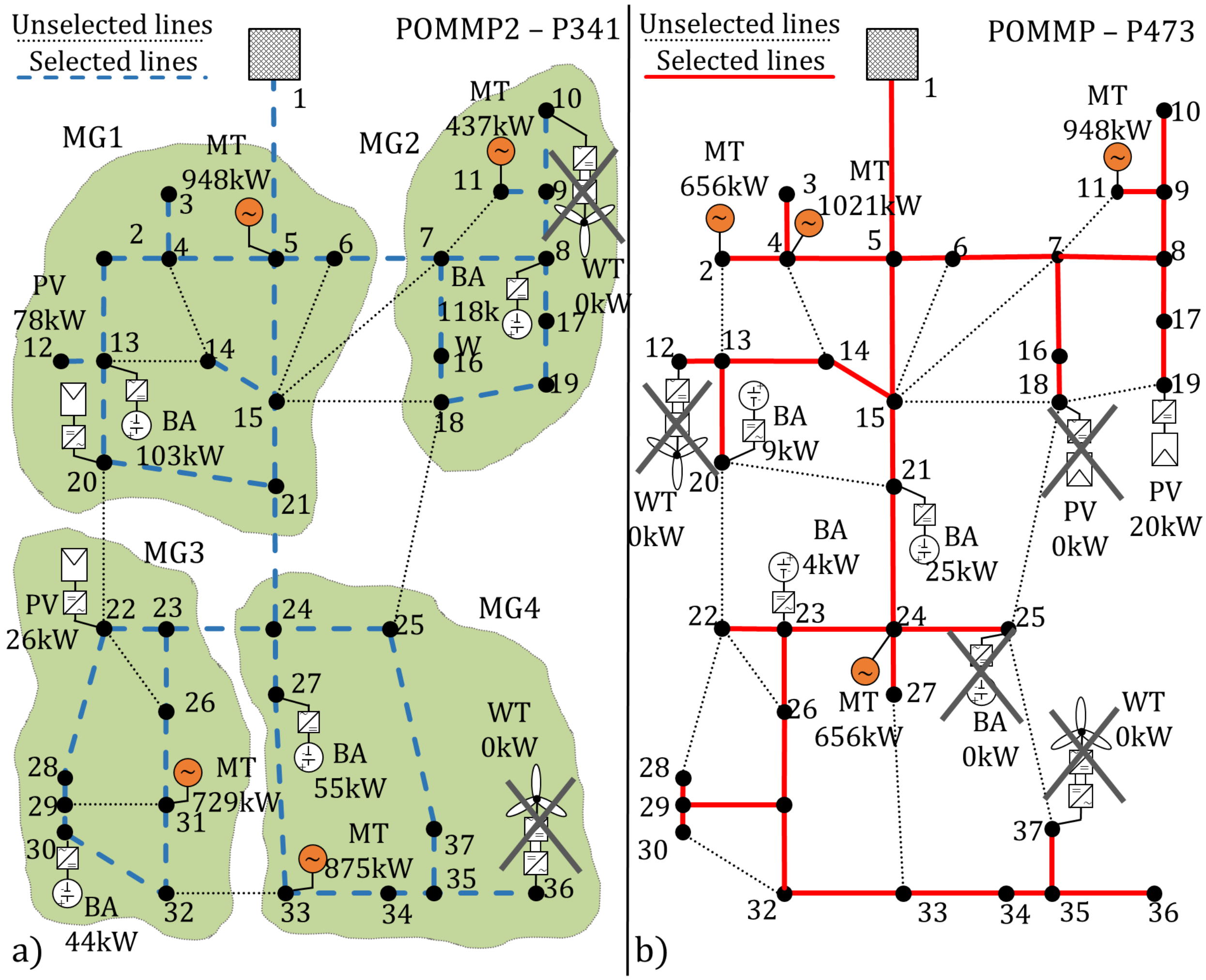

Figure 6-30.: a) Topology based on clusters; b) Radial-based topology, adapted from Contreras *et al.* (2020b)

future planning might evolve into more comprehensive methodologies, since the presence of a wider variety of DERs with different operating characteristics. Therefore, more comprehensive planning methodologies together an *a posteriori* analysis might offer the required tools for the future planning of microgrids and possibly other types of ADN.

The results with the CS2 support the hypothesis 2 (HS2) of this doctoral thesis. In this way, clear planning advantages were found with a more comprehensive holistic approach for planning simultaneously DERs' location and capacity together with the microgrid's topology.

On the other hand, one of the main characteristics of the proposed planning methodologies is the metaheuristic nature of the optimization models. Therefore, solutions to the planning problem cannot be seen as exact solutions but as sufficiently good solutions to the optimization problem. In other words, it is not possible to guarantee that the best solutions are found

with the proposed planning methodologies. On the contrary, solutions can be designated as "good enough" to provide good approximated solutions to practical problems where classical optimization algorithms cannot be used.
Therefore, the use of a true-multi-objective metaheuristic approach leads to trade-off criteria among the reached optimality, completeness, accuracy and precision of the solutions. Hence, the *a posteriori* analyze of the Pareto solutions for the microgrid planning problem gives rise to the argument that it is actually not necessary to find the best solution (optimality) when the metaheuristic solutions provide based on repetition a consistent confidence interval of the results for the POMMP and POMMP2 methodologies.
Furthermore, it is clear that infinite solutions for solving the multi-objective microgrid planning problem exist. This is a consequence of the mix-integer nature of the optimization problem that leads to infinite combinations of size and location of DERs together with the microgrid's topology configuration. However, it was found that several solutions might offer similar operation and planning conditions from the simulation results for the POMMP and POMMP2 methodologies, whose coverage is evaluated *a posteriori* based on the diversity of the Pareto solutions. Therefore, solutions from a proper selection of the metaheuristic optimization algorithm, variables and parameter tuning might guarantee sufficient completeness in the solutions to support the idea that not actually all solutions to accomplish a sufficient good final decision-making analysis under a particular planning preference setup are needed.
Nonetheless, different disadvantages are also identified and lead to space for improvements. For example, it was confirmed the highly case-dependency of the microgrid planning problem from the numerical results of the different case studies and planning scenarios presented above. Consequently, in some cases, it may be difficult to decide whether the optimal solutions found by the POMMP and POMMP2 methodologies are good enough, especially when it is implicit a lack of comparative references and alternative planning methodologies that comprehensively cover future required conditions. Therefore, improvements in the theory underlying heuristics and practical experiences may contribute to the accuracy and precision assessment of the results.
Moreover, although simulation results demonstrated the potential of the proposed planning methodologies, uncertainty in the output of the planning methodologies due to the model inputs may significantly affect the planning results. One example is the current simulation results for POMMP and POMMP2 where it was identified the relationship between the decision variables limits and the output values of the planning methodologies. Therefore, a careless review of the robustness of the results might become a problem, which should be carefully case-dependent analyzed from sensitivity.
These final remarks and global analysis of the results lead to the conclusion that POMMP and POMMP2 can be seen as potential novel planning tools with a young status for addressing future microgrid planning problems. Therefore, there is open a considerable space for further deep research and evaluations in order to achieve a solid status for possible successful applicability.

7. Concluding remarks and suggestions for future research

The electric power industry is currently facing a radical change in the whole energy supply landscape. This transformation has brought us into one of the major transition era in the electric power generation, transmission, distribution and sales paradigms with an unprecedented deployment of distributed energy resources (DER) within conventional local area power and energy systems. As a consequence, modern concepts, such as the microgrid concept, have appeared to facilitate the massive integration of DERs and future operation of the so-called decentralized electric power systems.

Modern and challenging design and operation features of microgrids and DERs have forced power and energy engineers, researchers, and stakeholders to radically rethink the way power distribution networks are traditionally planned, and more specifically, define novel methodologies for tackling the energy resources and network expansion planning problem in future microgrids and networked microgrids. In light of these challenges, in this doctoral thesis two versions of a Probabilistic Multi-objective Microgrid Planning methodology, i.e., POMMP and POMMP2, were proposed to find an answer to the research question and hypothesis formulated around the microgrid planning problem.

The doctoral thesis research process and results gave rise to three published journal papers, five presented and published conference proceedings, six bachelor thesis at the Universidad Nacional de Colombia, two versions of a mobility program between the EMC research group of the Universidad Nacional de Colombia and the IAT institute of the University of Bremen, Germany and opened up two current research topics for a master thesis at the IAT institute of the University of Bremen, Germany.

Concluding remarks for the research are presented in Section 7.1, while a general vision of the future of the microgrids from planning is offered in Section 7.2. Finally, some suggestions for future research are formulated in 7.3.

7.1. Concluding remarks

The two planning methodologies, POMMP and POMMP2, were formulated for optimally tackling modern challenges behind the decision-making for the optimal allocation of distributed energy resources under the paradigm of medium voltage microgrids and networked microgrids with capacity for exporting electricity and providing AS to the main grid (POMMP

and POMMP2 methodologies), and to simultaneously offer optimal planning solutions for microgrid's topology in a novel holistic approach (POMMP2 methodology).
The methodologies denote three main characteristics described below:

- The planning methodologies were developed based on a so-called true-multi-objective optimization model with a configurable set of three objective functions for the maximization of the available residual power for the AS provision, minimization of costs and minimization of the power losses in the microgrid. At the core of this dissertation, this punctual formulation is a novel proposal.

- A probabilistic technique based on the simulation of parameters from their associated probabilistic density function and by means of Monte Carlo Simulation was adopted for modeling the stochastic behavior in normal operating conditions of the non-dispatchable renewable generation resources and load demand as the main sources of uncertainties in the planning of microgrids.

- The second version of the methodology, POMMP2, proposed a novel strategy based on a bi-level optimization approach and multi-level graph partitioning technique for the planning of medium voltage networked microgrids from the holistic DERs allocation and cluster-based topology definition.

The methodologies were defined to consider a mixed generation matrix with dispatchable and non-dispatchable technologies, as well as distributed energy storage systems and conventional and power-electronic-based operation configurations depending on the technology (Chapter 3). In this way, mathematical models to represent the practical operation of microturbines, wind turbines, photovoltaic systems and battery systems were used for the POMMP and POMMP2 methodologies.
Conclusions drawn from Chapter 3 led to describe the minimum number of elements that must compose proper mathematical modeling for solving the microgrid planning problem. These were grouped in microgrid's components, distribution network, uncertainties, operation and economic framework.
Microgrid's components can considerably variate based on the base case and case study for the planning problem. However, they can be mainly grouped into dispatchable, non-dispatchable and energy storage components. The relevant impact of the dispatchable generation and energy storage components in the planning problem was found from the results in this research. For example, dispatchable units were required to simulate the power balance of the microgrid during the planning problem and energy storage resources were used to simulate operation strategies of the microgrid for the provision of AS and export of electricity to the main grid.
The results and comparison of the market conditions in Case study 1 (CS1) offered relevant variations on the planned capacity of the battery systems. Thus, due to batteries being able

to introduce flexibility to the microgrid's operation, the operation will be directly impacted by the provision of services to the main grid. The size of the batteries is strongly influenced by planning as it was found in the results between CAISO and PJM markets.

The results for the planning of networked microgrids in Case study 2 (CS2) showed the influence of the dispatchable units in the planning of these systems. One of the main characteristics of microgrids compared with other local area power systems, such as Smart Power Cells, is their capacity of operating in islanded mode. In this way, microgrids would be able to guarantee a stable operation during a certain period. This requirement is not possible to accomplish without dispatchable units. This characteristic was especially relevant for the planning of a networked microgrid or cluster-based microgrid in the CS2. For example, a tendency to group the dispatchable units when the cluster formation and topology definition are not considered during the planning stage was found.

The effect of the uncertainties in the renewable generation and the used mathematical models were also visualized in the planning results with POMMP and POMMP2. For example, visible differences were found between the total planned installed capacity and actual generated capacity in the results for the CS1. Therefore, uncertainties are also fundamental for calculating the global effective energy transformation and available power from renewable resources calculation. In this way, the size and location of the renewable generation with intermittent, variable and limited predictable operation is planned considering the stochastic local climate conditions and to compensate their lack or excess of power with the non-stochastic generation and storage technologies.

Simulation results in this dissertation supported the assumptions and strategies proposed for the definition of the optimization problem in Chapter 4. For instance, the proposal of a three-objective optimization problem, where the available residual power for the provision of AS services and the micrigrid's operation cost were considered essential, while a third objective was proposed as an adaptable objective function to evaluate different characteristics of the microgrid, led to analyze advantages in the decision making over the microgrid planning problem solution. One example of this conclusion can be found in the behavior of the Pareto solution set during the parameter and variables limit tuning (Chapter 6). It was found that the convergence of the Pareto solutions is initially determined in terms of the average power losses. Furthermore, relevant advantages in terms of the power losses and the use of the POMMP2 methodology were found in CS2.

The results in Chapter 6 showed the advantages of a true-multi-objective problem, which brings about the possibility of decision-making by the stakeholder based on a trade-off among the optimal Pareto solutions. In this way, the optimal allocation DERs have led to improvements on the energy losses while the microgrid can maintain a reserve of active power to be transferred back to the main grid as required. This type of conclusion is specially relevant since the final shape and trade-off of the solutions in the Pareto set are impossible to known *a priori* in practical engineering problems.

The results obtained from the evaluation of the formulated case studies with two different markets showed the relevance of an *a posteriori* analysis of the alternatives for the decision-making in the solution of the microgrid planning problem. Consequently, it was possible to visualize the dependency of microgrid planning on the territory (market) in which the microgrid is defined since the market and its policies will determine how viable or not it is to provide AS. For example, for the CS1 and the planning scenarios under the PJM and CAISO markets, it was observed that the supply of AS by the microgrid under the CAISO market conditions is equal to zero as it is more profitable to only sell energy to the wholesale market. An opposite outcome was found with the PJM market where there was a revenue stream for supplying AS. It was also observed that the important role of the DERs location was displayed in the results at the moment to select one optimal solution in the multi-criteria decision making. For example, it was clear the significant impact of the DERs location on the power flow, average daily residual energy and operating cost.

It is concluded from the results of the CS2 in Chapter 6 that more comprehensive planning methodologies such as POMMP2 offers clear advantages regarding traditional separated approaches such as with the POMMP. For example, microgrid losses can be reduced with an optimal loop-based topology compared with a radial-based one for similar residual power capacity. Moreover, the available residual power can significantly increase with the increase of the generation portfolio, where dispatchable units have a relevant role to benefit the islanded operation.

7.2. A general vision of the future of microgrids from the planning perspective

Decentralized power grids are envisioned as the future of the electric power industry. In this context, concepts such as microgrids have attracted special attention as well as the planning methodologies used for effective deployment of this type of active distribution network. Therefore, this dissertation has explored and drawn key conclusions regarding the future of the microgrids from the planning perspective.

Accordingly, in Chapter 2 of this dissertation, a deep conceptual framework for the deployment of microgrids was studied and presented. These characteristics led to the definition of four key features for the future microgrid planning methodologies, which were the core for the POMMP and POMMP2 methodologies formulation and whose relevance was supported on the simulation results presented in this dissertation.

In this vein, the future of the microgrids from the planning perspective will involve multiple objectives to effectively exploit the microgrid's benefits. Furthermore, microgrid are expected to become essential to provide services to the main grid. Therefore, microgrid planning methodologies will have to incorporate value streams as part of the planning objectives. Moreover, those advantages would be evaluated in an *a posteriori* decision-making process, as it was seen in the simulation results of this dissertation.

It is also envisioned that certain types of microgrids, such as medium voltage utility or networked microgrids will become more attractive for investors and stakeholders. This is supported from the possibility of accomplishing an integral microgrid system with advantages such as the one from the services provision and technical enhancements (e.g. reduction of power losses). This was visualized in the simulation results for the two case studies, where a base network (passive distribution network) might be planned with a complete installed capacity to participate in the electric markets. However, it was found from results, that this characteristic would be accompanied by a parallel development of liberalized markets (and local markets) for active participation of microgrids and other local area power and energy systems.

7.3. Suggestions for future research

The proposed planning methodologies, statements, assumptions, methods, models, and simulation results in this doctoral thesis opened a wide range of new possibilities for future research in the area. This doctoral research makes it clear that the research line on short, medium and long term planning of microgrids and other local area active distribution networks has several gaps that still need to be filled. Furthermore, the methodologies proposed in this doctoral thesis are presented as novel, so they are potential tools still in a young state that requires continuation and further research.
In this context, a chosen set of strategic research lines and themes are listed below.

- Future research can be related to the optimal planning of resources under the same planning methodology frameworks to supply other types of AS such as non frequency-based AS: Black start capability, reactive supply and voltage control, island operation capabilities, inertia for local grid stability, fast reactive current injection and short circuit current.

- A wide range of technical questions about the microgrid and main grid stability from the planning step will lead to future research for extending flexible planning methodologies such as POMMP or POMMP2.

- The impact of the uncertainty modeling techniques should be deeper researched and compared.

- Microgrid planning methodologies in the future should consider a greater interaction of the microgrid with the main grid from the planning stage. Therefore, research about multi-objective power resources planning framework for an optimal internal mismatch and cross-voltage-level power transfer in microgrids with ancillary services capacity should be addressed.

- Finally, it is expected that methodologies as POMMP can be tested under different market conditions, networks and case studies in order to identify open market features that can benefit the microgrid's revenue streams and hence to support their implementation.

List of publications

Status on August 20, 2020

Articles in international journals

- Contreras, S.F., Cortes, C.A., and Myrzik, J.M.A. (2020). "Probabilistic Multi-objective Microgrid Planning Methodology for Optimizing the Ancillary Services Provision". Electric Power Systems Research, Vol. 189, pp. 106633. doi: https://doi.org/https://doi.org/10.1016/j.epsr.2020.106633.
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- Cortes, C. A., Contreras, S. F., and Shahidehpour, M. (2018). "Microgrid Topology Planning for Enhancing the Reliability of Active Distribution Networks." IEEE Transactions on Smart Grid, Vol. 9, No. 6, pp. 6369-6377. doi: https://doi.org/10.1109/TSG.2017.2709699.

Publications during doctoral research not included in this dissertation

- Hinker, J., Wohlfahrt, T., Drewing, E., Contreras Paredes, S.F., Mayorga González, D., and Myrzik, J.M.A. (2018). "Adaptable Energy Systems Integration by Modular, Standardized and Scalable System Architectures: Necessities and Prospects of Any Time Transition". Energies, Vol. 11, No. 3 pp.581. doi: https://doi.org/10.3390/en11030581.

Conference contributions, published in full in the conference proceedings

- Contreras, S.F., Cortes, C.A., and Myrzik, J. M. A. (2020). "Probabilistic Multi-objective Microgrid Planning Methodology for Optimizing the Ancillary Services Provision". In 2020 Power Systems Computation Conference (PSCC).

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- Acosta, A.F., Contreras, S.F., and Cortés, C.A. (2018). "Performance Assessment of a Modified Multi-objective Cuckoo's Search Algorithm for Microgrid Planning Considering Uncertainties". Proceedings of the Genetic and Evolutionary Computation Conference Companion on - GECCO'18, 276–277. doi: https://doi.org/10.1145/3205651.3205728.

Publications during doctoral research not included in this dissertation

- Hinker, J., Contreras, S.F., and Myrzik, J.M.A. (2018). "An Adaptable System Architecture for Modular, Standardized and Scalable Urban Energy Systems". CIRED 2018 Ljubljana Workshop, pp. 1–4. doi: https://doi.org/10.34890/172.

Projects and supervised thesis

Status on August 20, 2020

Cooperation projects

- Design of Microgrids for Enhancing the Reliability of Remote Electric Grids in Colombia – DEMEREG. PROCOL/PPP Program, Colciencias-DAAD, 2020-2021.
- Planning and Operation of microgrids for the modernization of the Colombian Electric Grid – POMCEG. PROCOL/PPP Program, Colciencias-DAAD, 2017-2018.

Supervised bachelor thesis

- Lopez Rivera, D.F. and Rodríguez Bejarano, M.A. (2019). "Implementación y evaluación del desempeño del algoritmo MOEA/D para el problema de planificación de una microrred". Departamento de Ingeniería Eléctrica y Electrónica, Universidad Nacional de Colombia, Bogotá D.C., Colombia.
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A. Appendix: Test systems benchmarks data

In this appendix, technical information regarding the PG&E 69-bus and IEEE 37-bus test systems are presented.

A.1. PG&E 69-bus Medium voltage distribution network test system data

A.1.1. General Characteristics data

The PG&E 69-bus test systems is a MV three-phases radial-based passive distribution network. The system represent a portion of an actual PG&E distribution network in the USA. Therefore, the system's structure follow typical North American three-phase medium voltage distribution feeders, in this case with radial structure since these are prevalent. The nominal voltage on the three-phase sections is 12.66 kV and the system frequency is 60 Hz.
The test system is considered symmetrical based on efforts to balance the loading. However, in reality due to the existence of single-phase laterals, the North American MV network configuration is inherently unbalanced.
The line types are normally overhead lines that are used with bare conductors made of aluminum with or without steel reinforcement, i.e. AAC and ACSR., while the majority of North American networks are solidly grounded.
The details of the base case are described in Savier and Das (2007) and Baran and Wu (1989), and the adaptation was made based on Arefifar and Mohamed (2014b,a).

Table A-1.: Network data for the PG&E 69-bus test system

Line segment	Bus from	Bus to	R [Ω]	X [Ω]	Line segment	Bus from	Bus to	R [Ω]	X [Ω]
1	1	2	0,0005	0,0012	35	3	59	0,0044	0,0108
2	2	3	0,0005	0,0012	36	59	60	0,064	0,1565
3	3	4	0,0015	0,0036	37	60	61	0,1053	0,123
4	4	5	0,0251	0,0294	38	61	62	0,0304	0,0355
5	5	6	0,366	0,1864	39	62	63	0,0018	0,0021
6	6	7	0,381	0,1941	40	63	64	0,7283	0,8509
7	7	8	0,0922	0,047	41	64	65	0,31	0,3623
8	8	9	0,0493	0,0251	42	65	66	0,041	0,0478
9	9	10	0,819	0,2707	43	66	67	0,0092	0,0116
10	10	11	0,1872	0,0619	44	67	68	0,1089	0,1373
11	11	12	0,7114	0,2351	45	68	69	0,0009	0,0012
12	12	13	1,03	0,34	46	4	36	0,0034	0,0084
13	13	14	1,044	0,345	47	36	37	0,0851	0,2083
14	14	15	1,058	0,3496	48	37	38	0,2898	0,7091
15	15	16	0,1966	0,065	49	38	39	0,0822	0,2011
16	16	17	0,3744	0,1238	50	8	40	0,0928	0,0473
17	17	18	0,0047	0,0016	51	40	41	0,3319	0,1114
18	18	19	0,3276	0,1083	52	9	42	0,174	0,0886
19	19	20	0,2106	0,069	53	42	43	0,203	0,1034
20	20	21	0,3416	0,1129	54	43	44	0,2842	0,1447
21	21	22	0,014	0,0046	55	44	45	0,2813	0,1433
22	22	23	0,1591	0,04526	56	45	46	1,59	0,5337
23	23	24	0,3463	0,1145	57	46	47	0,7837	0,263
24	24	25	0,7488	0,2475	58	47	48	0,3042	0,1006
25	25	26	0,3089	0,1021	59	48	49	0,3861	0,1172
26	26	27	0,1732	0,0572	60	49	50	0,5075	0,2585
27	3	28	0,0044	0,0108	61	50	51	0,0974	0,0496
28	28	29	0,064	0,1565	62	51	52	0,145	0,0738
29	29	30	0,3978	0,1315	63	52	53	0,7105	0,3619
30	30	31	0,0702	0,0232	64	53	54	1,041	0,5302
31	31	32	0,351	0,116	65	11	55	0,2012	0,0611
32	32	33	0,839	0,2816	66	55	56	0,0047	0,0014
33	33	34	1,708	0,5646	67	12	57	0,7394	0,1444
34	34	35	1,474	0,4873	68	57	58	0,0047	0,0016

A.1.2. Network data

In the USA rural distribution networks, normally conductors are mounted on towers as overhead lines. However, this information is not available for the test system. The network data is presented in Table **A-1**

Table A-2.: Load data for the PG&E 69-bus test system

Bus	P [kW]	Q [kVAr]	S [kVA]	PF	Bus	P [kW]	Q [kVAr]	S [kVA]	PF
6	2,6	2,2	3,4	0,76	38	384,7	274,5	472,6	0,81
7	40,4	30	50,3	0,80	39	384,7	274,5	472,6	0,81
8	75	54	92,4	0,81	40	40,5	28,3	49,4	0,82
9	30	22	37,2	0,81	41	3,6	2,7	4,5	0,80
10	28	19	33,8	0,83	42	4,35	3,5	5,6	0,78
11	145	104	178,4	0,81	43	26,4	19	32,5	0,81
12	145	104	178,4	0,81	44	24	17,2	29,5	0,81
13	8	5	9,4	0,85	48	100	72	123,2	0,81
14	8	5,5	9,7	0,82	50	1244	888	1528,4	0,81
16	45,5	30	54,5	0,83	51	32	23	39,4	0,81
17	60	35	69,5	0,86	53	227	162	278,9	0,81
18	60	35	69,5	0,86	54	59	42	72,4	0,81
20	1	0,6	1,2	0,86	55	18	13	22,2	0,81
21	114	81	139,8	0,82	56	18	13	22,2	0,81
22	5	3,5	6,1	0,82	57	28	20	34,4	0,81
24	28	20	34,4	0,81	58	28	20	34,4	0,81
26	14	10	17,2	0,81	59	26	18,55	31,9	0,81
27	14	10	17,2	0,81	60	26	18,55	31,9	0,81
28	26	18,6	32,0	0,81	62	24	17	29,4	0,82
29	26	18,6	32,0	0,81	63	24	17	29,4	0,82
33	14	10	17,2	0,81	64	1,2	1	1,6	0,77
34	19,5	14	24,0	0,81	66	6	4,3	7,4	0,81
35	6	4	7,2	0,83	68	39,22	26,3	47,2	0,83
37	79	56,4	97,1	0,81	69	39,22	26,3	47,2	0,83
					TOTAL	3801,89	2694,1	4660,4	0,82

A.1.3. Load data

The network load data is presented in Table **A-2**.

A.2. IEEE 37-bus Medium voltage distribution network test system data

A.2.1. General Characteristics data

The IEEE 37-bus Test Feeder is a three-phase delta ungrounded underground MV radial-based passive distribution system. The system has delta connected spot loads with a mixture of constant PQ (constant Z and I). The lines are all delta underground line segments with a so-called configuration 722 between bus 1-5, and 723 for all others Kersting (1991); IEEE PES (2020). The nominal voltage on the three-phase test feeder is 4.8 kV and the system frequency is 60 Hz.

The test system is proposed in Kersting (1991); IEEE PES (2020). However, the set of connection options and distances are adopted from Cortes *et al.* (2018); Che *et al.* (2017b) as shown in Figure **A-1**

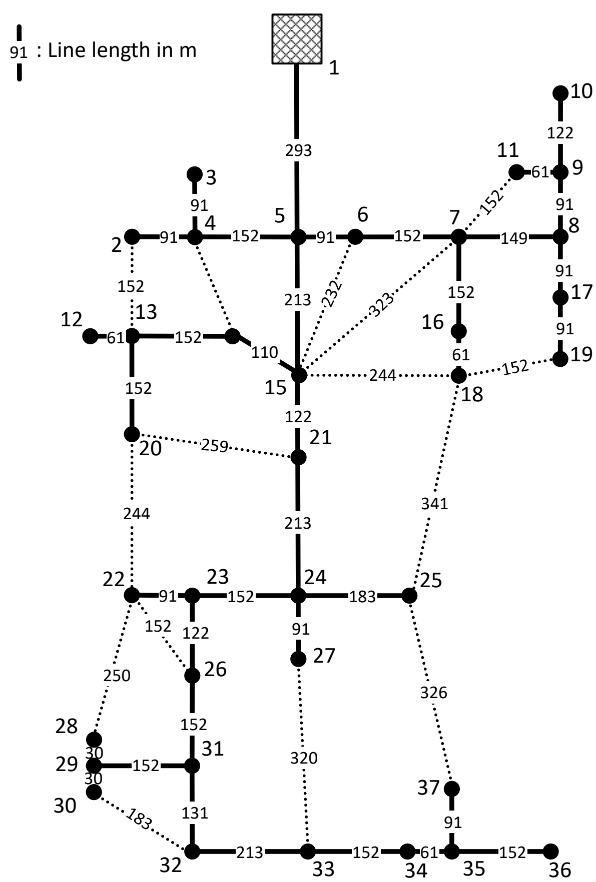


Figure A-1.: Test system IEEE-37 bus adapted based on Che *et al.* (2017b)

A.2.2. Network data

The network data is presented in Table **A-3**. The resistance, reactance and succeptance values are presented in terms of the distances in Figure **A-1** and the balanced case for lines configuration 722 for the segment 1 between buses 1 and 5, and configuration 723 for the other line segments. The line configurations are consigned in Table **A-4**.

Table A-3.: Network data for the IEEE 37-bus test system

Line segment	Bus from	Bus to	R [Ω]	X [Ω]	B [μ S]	Line segment	Bus from	Bus to	R [Ω]	X [Ω]	B [μS]
1	1	5	0,1126	0,2330	76,2530	27	18	25	0,0738	0,0654	15,8753
2	2	13	0,0330	0,0292	7,0872	28	18	19	0,0330	0,0292	7,0872
3	4	14	0,0356	0,0315	7,6541	29	20	21	0,0560	0,0496	12,0482
4	4	2	0,0198	0,0175	4,2523	30	20	22	0,0527	0,0467	11,3395
5	4	3	0,0198	0,0175	4,2523	31	21	24	0,0461	0,0408	9,9220
6	5	15	0,0461	0,0408	9,9220	32	22	28	0,0540	0,0478	11,6230
7	5	4	0,0330	0,0292	7,0872	33	22	26	0,0330	0,0292	7,0872
8	5	6	0,0198	0,0175	4,2523	34	23	26	0,0264	0,0233	5,6697
9	6	15	0,0501	0,0443	10,7725	35	23	22	0,0198	0,0175	4,2523
10	6	7	0,0330	0,0292	7,0872	36	24	25	0,0395	0,0350	8,5046
11	7	15	0,0699	0,0619	15,0248	37	24	23	0,0330	0,0292	7,0872
12	7	8	0,0323	0,0286	6,9454	38	25	37	0,0705	0,0624	15,1665
13	7	11	0,0330	0,0292	7,0872	39	26	31	0,0330	0,0292	7,0872
14	7	16	0,0330	0,0292	7,0872	40	27	33	0,0692	0,0613	14,8830
15	8	9	0,0198	0,0175	4,2523	41	27	24	0,0198	0,0175	4,2523
16	8	17	0,0198	0,0175	4,2523	42	29	28	0,0066	0,0058	1,4174
17	9	10	0,0264	0,0233	5,6697	43	29	30	0,0066	0,0058	1,4174
18	9	11	0,0132	0,0117	2,8349	44	30	32	0,0395	0,0350	8,5046
19	13	12	0,0132	0,0117	2,8349	45	31	32	0,0283	0,0251	6,0950
20	13	20	0,0330	0,0292	7,0872	46	31	29	0,0330	0,0292	7,0872
21	14	13	0,0330	0,0292	7,0872	47	32	33	0,0461	0,0408	9,9220
22	15	18	0,0527	0,0467	11,3395	48	33	34	0,0330	0,0292	7,0872
23	15	21	0,0264	0,0233	5,6697	49	34	35	0,0132	0,0117	2,8349
24	15	14	0,0237	0,0210	5,1028	50	35	36	0,0330	0,0292	7,0872
25	16	18	0,0132	0,0117	2,8349	51	35	37	0,0198	0,0175	4,2523
26	17	19	0,0198	0,0175	4,2523						

Table A-4.: Line configurations 722 and 723

Line Configuration 722 - Line segment 1								
Z (R +jX) in ohms per kilometer						B in micro Siemens per kilometer		
R [Ω/km]	jX [Ω/km]	R [Ω/km]	jX [Ω/km]	R [Ω/km]	jX [Ω/km]	B [μS/km]	B [μS/km]	B [μS/km]
0,29521	0,18473	0,10122	-0,02026	0,07668	-0,03772	79,43023	0	0
0	0	0,27887	0,16640	0,10122	-0,02026	0	79,43023	0
0	0	0	0	0,29521	0,18473	0	0	79,43023
Balanced $\mathrm{Z} = 0,11731 + \mathrm{j}0.24371$ [Ω/km]						**Balanced** $\mathrm{B} = 79,43023$ [μS/km]		
Line Configuration 723 - Line segments 2 to 51								
Z (R +jX) in ohms per kilometer						**B in micro Siemens per kilometer**		
R [Ω/km]	**jX [Ω/km]**	**R [Ω/km]**	**jX [Ω/km]**	**R [Ω/km]**	**jX [Ω/km]**	**B [μS/km]**	**B [μS/km]**	**B [μS/km]**
0,80381	0,41713	0,30267	0,13117	0,28490	0,09451	46,50372	0	0
0	0	0,80915	0,39308	0,30267	0,13117	0	46,50372	0
0	0	0	0	0,80381	0,41713	0	0	46,50372
Balanced $\mathrm{Z} = 0,21624 + \mathrm{j}0.19144$ [Ω/km]						**Balanced** $\mathrm{B} = 46,50372$ [μS/km]		

A.2.3. Load data

The network load data is presented in Table A-5.

Table A-5.: Load data for the IEEE 37-bus test system

Bus	P [kW]	Q [kVAr]	S [kVA]	PF	Bus	P [kW]	Q [kVAr]	S [kVA]	PF
2	93	44	102,9	0,90	20	126	63	140,9	0,89
3	85	40	93,9	0,90	21	85	40	93,9	0,90
6	85	40	93,9	0,90	22	42	21	47,0	0,89
8	85	40	93,9	0,90	25	85	40	93,9	0,90
10	42	21	47,0	0,89	26	85	40	93,9	0,90
11	161	80	179,8	0,90	28	42	21	47,0	0,89
12	42	21	47,0	0,89	30	85	40	93,9	0,90
13	42	21	47,0	0,89	31	42	21	47,0	0,89
14	42	21	47,0	0,89	32	140	70	156,5	0,89
16	38	18	42,0	0,90	33	126	62	140,4	0,90
18	85	40	93,9	0,90	36	42	21	47,0	0,89
19	42	21	47,0	0,89	37	85	40	93,9	0,90
					TOTAL	1827	886	2030,5	0,90

B. Appendix: Simulation and time series data

The POMMP and POMMP2 methodologies include a probabilistic technique for modeling uncertainties in the operation of the renewable technologies and load demand. In this appendix the readers can find a summary of the information used for the simulations in Chapter 6.

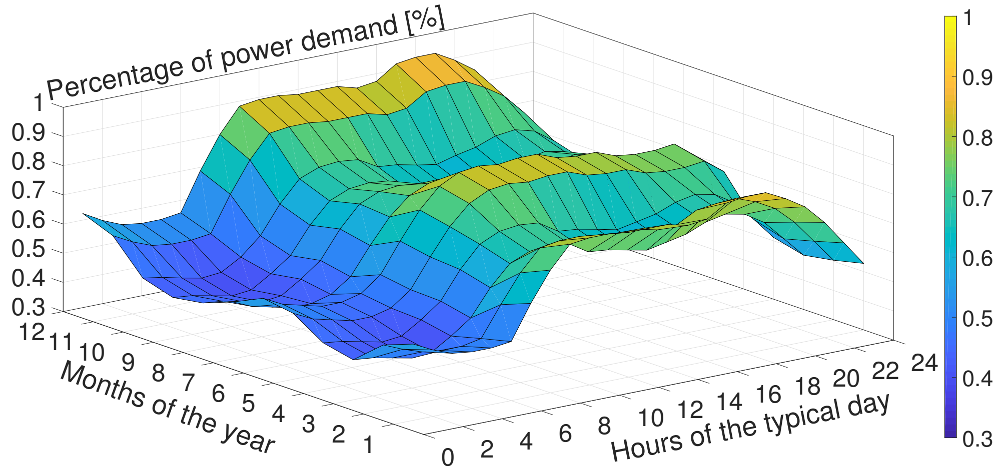
B.1. Load demand data

The load demand data is based on the load model in (Probability Methods Subcommittee, 1979). The values are organized chronologically so that daily, weekly and seasonal patterns can be modeled. The hourly peak load is given by weekday and weekend and suggest a pattern for the winter season between week 1-8 and 44-52, summer season between week 18-30 and spring/fall seasons between week 9-17 and 31-43. An overview of the load pattern for three typical days per month (weekday, weekend and peak day) along the planning horizon is shown in Figure **B-1**.

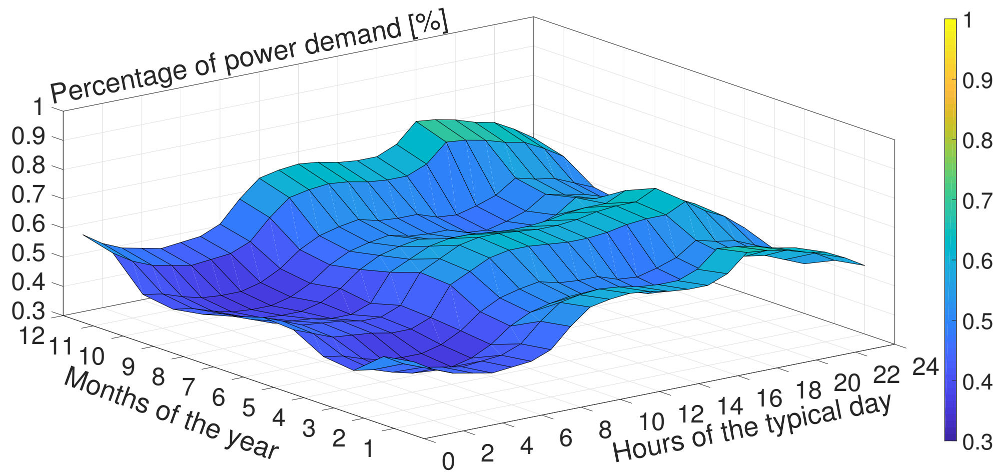
The percentage of the typical days are constructed based on the hourly average value of the load demand percentage for the monthly weekday and weekend, while the peak day is selected as the day in the month with the highest average percentage value of power demand. The data is included in Figure **B-1**. Furthermore, time series are constructed with a random variation of $\pm$ 1% for simulating three years of load demand record. The time series can be consulted. The time series data can be accessed in (Contreras *et al.*, 2020a).

B.2. Climate historical data

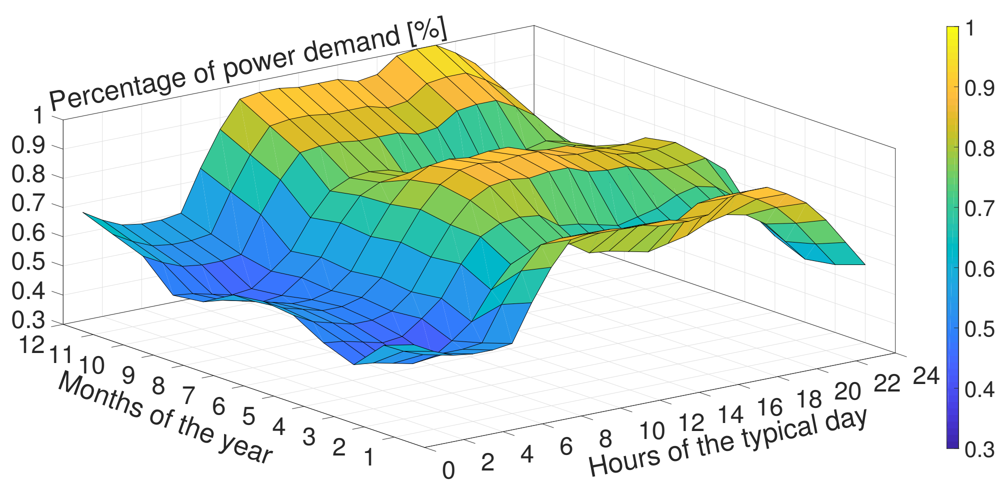
Wind and solar historical data have been strategically chosen from the German Meteorological Office (*Deutscher Wetterdienst-DWD*) for the simulations in this dissertation. Time series with a resolution of one hour and a period of three years was used from the city of Kiel in Germany.



(a)



(b)



(c)

Figure B-1.: Pattern of the load demand along the planning horizon. a) Weekday, b) Weekend, c) Peak day

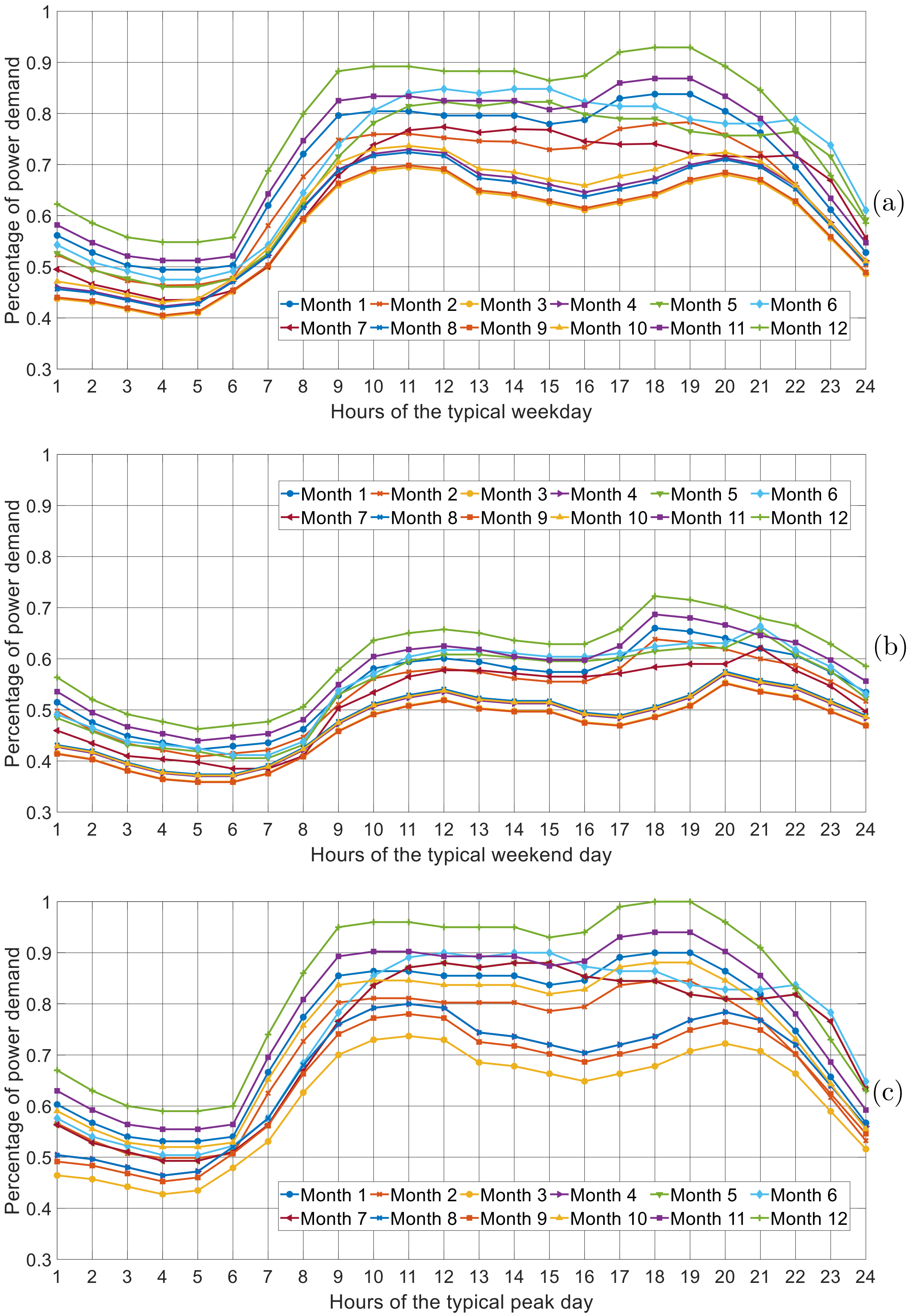


Figure B-2.: Data of the load demand along the planning horizon. a) Weekday, b) Weekend, c) Peak day

B.2.1. Time series of the wind speed

An overview of the time series for the wind speed in the city of Kiel, Germany, can be visualized in Figure B-3. The values are shown in periods of 24 hours during a year as the average value among the total time series data for three years, and the measurements are done in a 116m high point.

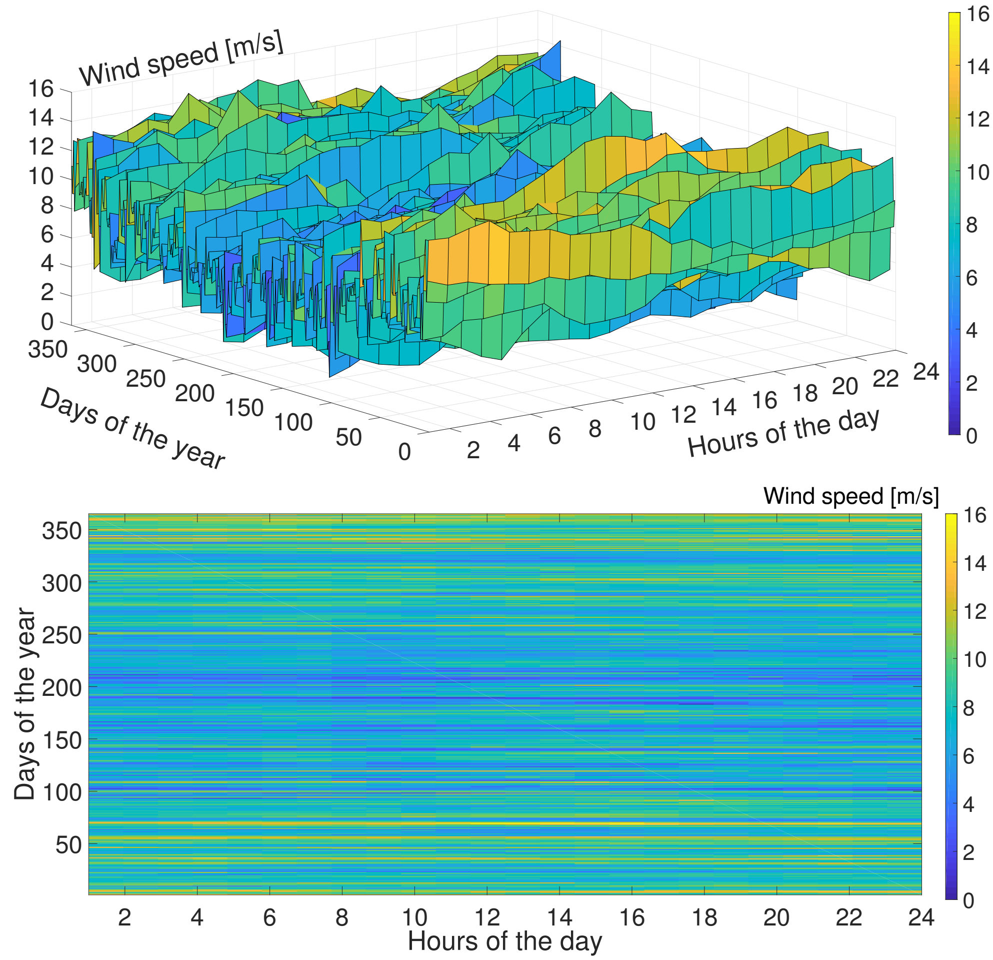


Figure B-3.: Overview of the wind speed behavior in the Kiel city, Germany

The specific time series for the wind speed can be accessed in (Contreras *et al.*, 2020a). An example of the histograms and Weibull PDF for the 12:00h of a typical day of a month in winter, spring, summer and fall are presented in Figure B-4.
The resulting Weibull PDF for the showed typical seasonal days are shown in Figure B-5. Furthermore, the suitability of the Weibull PDF for the wind speed time series is verified as it is shown in Figure B-6.
With the Weibull probability plot in Figure B-6, the wind speed data is assessed visually whether comes from a population with a Weibull distribution. Therefore, since then the

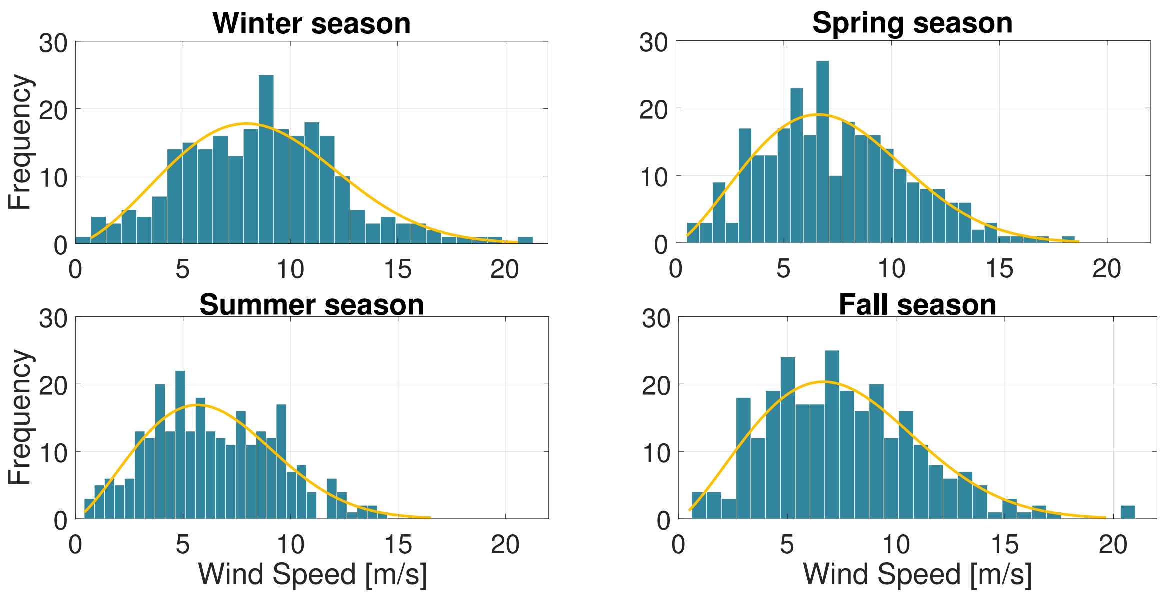


Figure B-4.: Frequency diagrams for the wind speed in a typical seasonal day at 12:00h

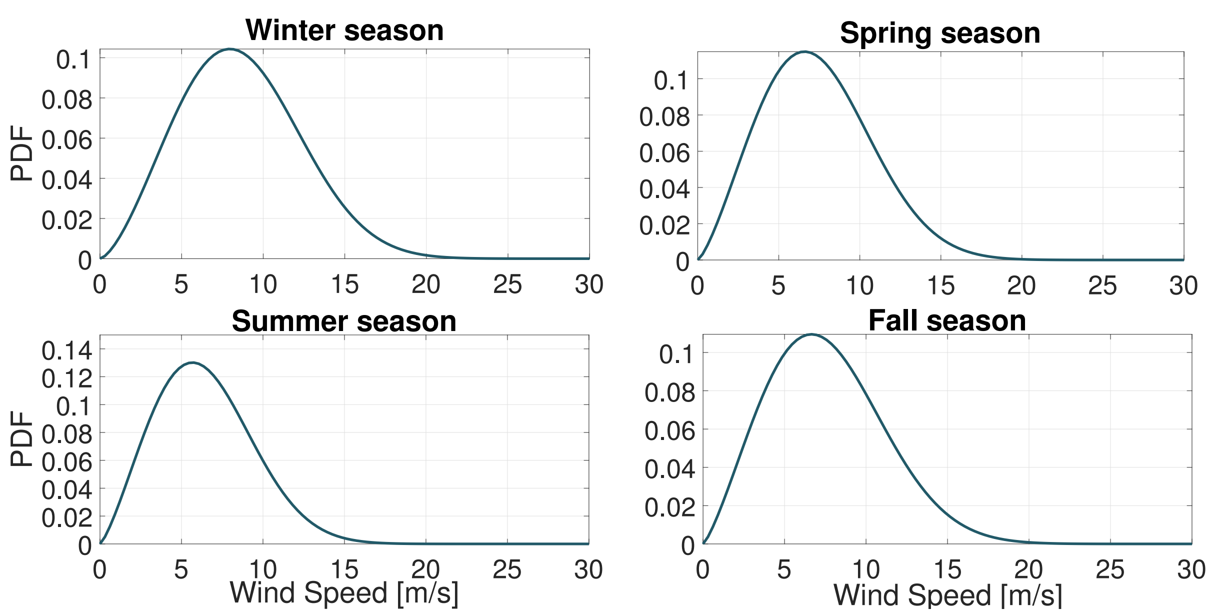


Figure B-5.: Weibull PDF for the wind speed in a typical seasonal day at 12:00h

data fall along the reference line, the wind data has a Weibull distribution.

The y-axis of the Weibull probability plot represents the quantiles of the Weibull distribution as probability values (accumulative probability). The wind speed time series data is sorted and scaled logarithmically.

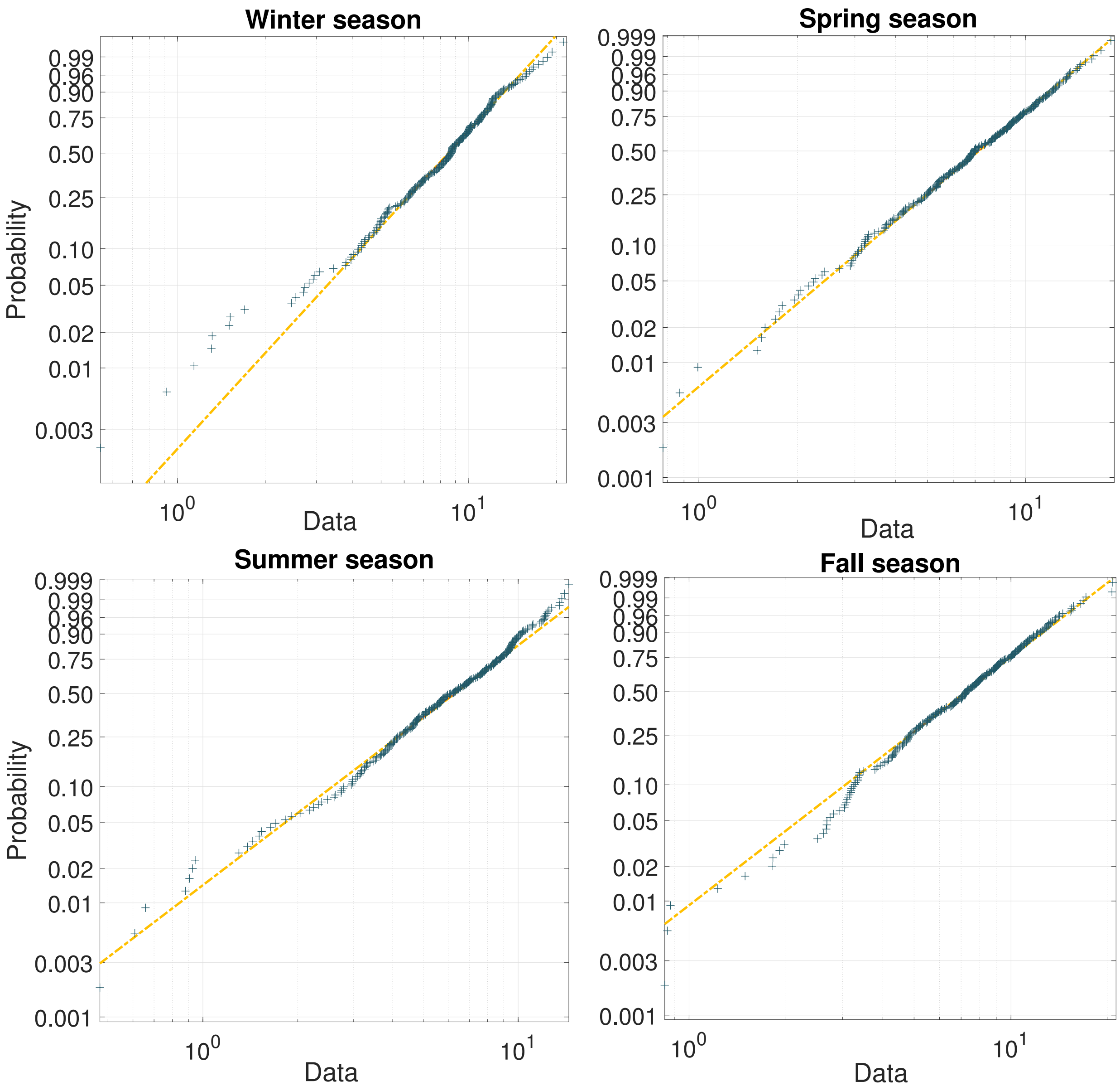


Figure B-6.: Weibull probability plot for the wind speed in a typical seasonal day at 12:00h

B.2.2. Time series of the solar irradiation

An overview of the time series for the global solar irradiance in the Kiel city in Germany can be visualized in Figure B-7. The values are shown in periods of 24 hours during a year as the average value among the total time series data for three years. The global solar irradiance is measured over the ground level and calculated as the sum of the direct irradiance and diffuse horizontal irradiance.

The specific time series for the solar irradiation can be accessed in (Contreras *et al.*, 2020a). The selection of the PDF for the solar irradiance is a strongly case-dependence task. For

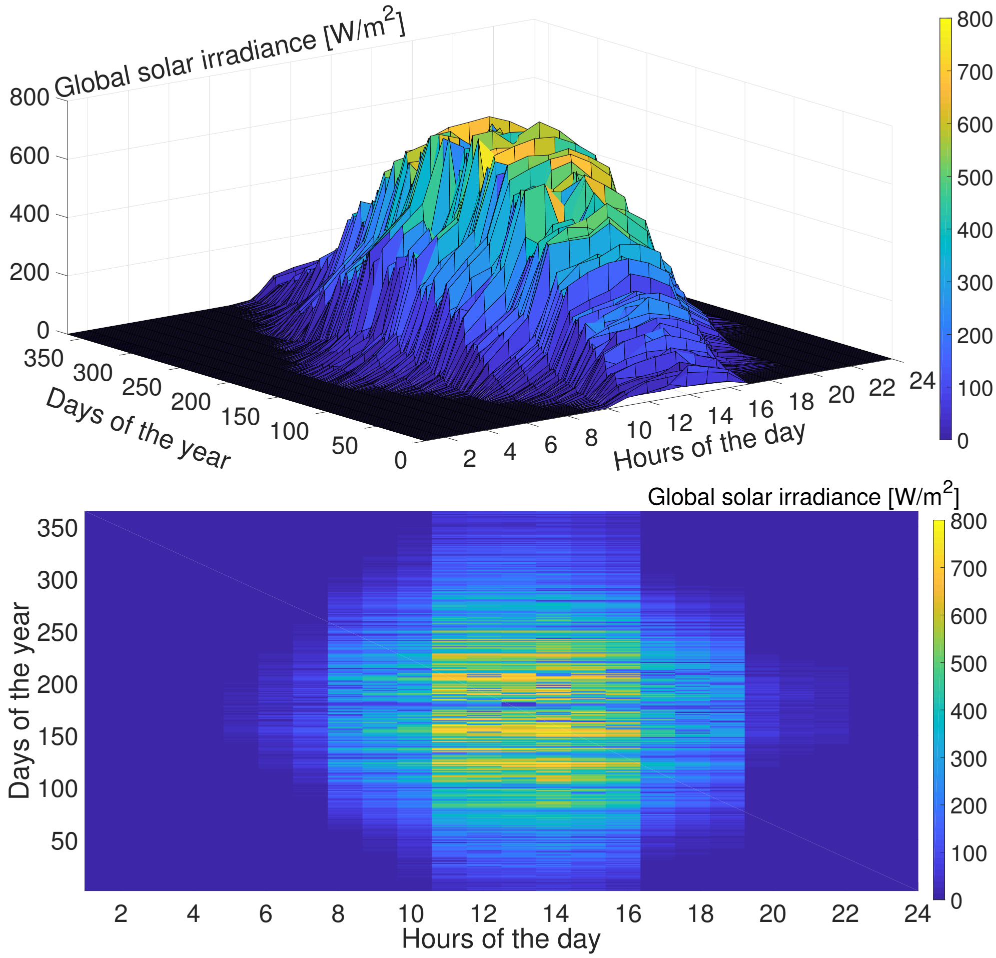


Figure B-7.: Overview of the solar irradiance behavior in the Kiel city, Germany

example, the PDF for the time series of a typical day of a month in winter, spring, summer and fall can be seen in Figure **B-8**. In this case, the Beta PDF function suits to represent the solar irradiation data.

However, the probabilistic model in the POMMP and POMMP2 methodologies consider time steps of one hour for the PDF definition. In this case, an example of the histograms for the 12:00h in a typical day of a month in winter, spring, summer and fall are presented in Figure **B-9**.In this case, a Log-normal PDF cound be defined as in Figure **B-10**.

In this case, although the Log-normal PDF can be used, this has more deficient fitting compared with the Weibull PDF for the wind speed. Different PDF can be tried based on the time series in (Contreras *et al.*, 2020a)

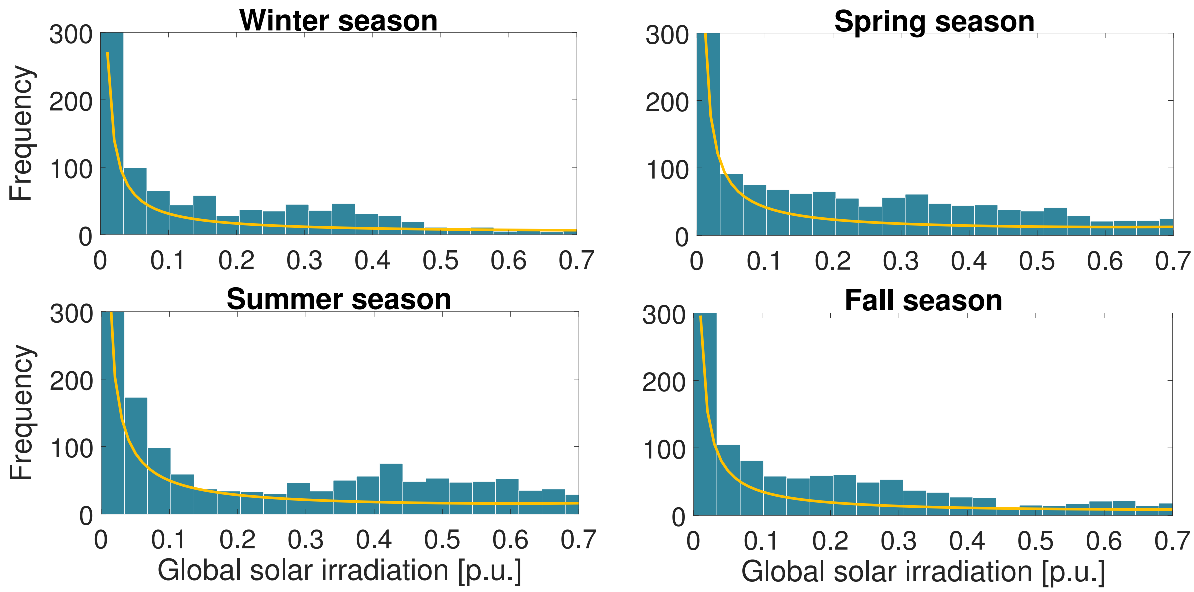


Figure B-8.: Frequency diagrams for the global solar irradiation in a typical seasonal day

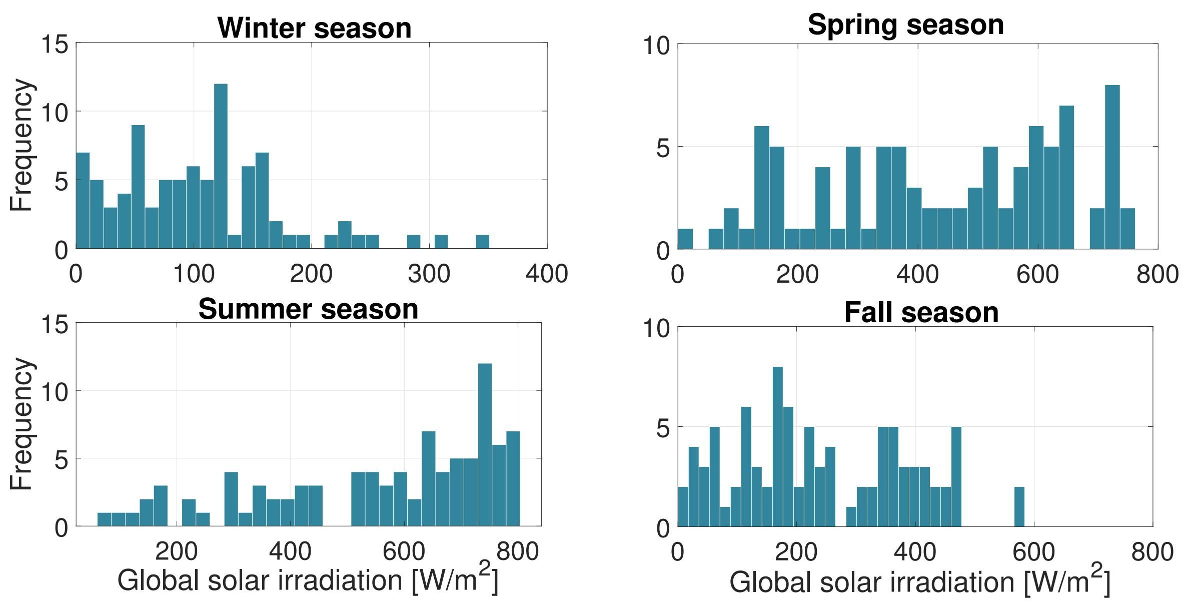


Figure B-9.: Frequency diagrams for the global solar irradiation in a typical seasonal day at 12:00h

B.3. Electrical market and economical data

The economic data used to describe the PJM and CAISO market were obtained in (Stadler, 2008) and (IRENA, 2014). The time series of the tariff for exporting energy to the main utility grid (T_{Ex}) were based on the clearing price of the market. The clearing prices used

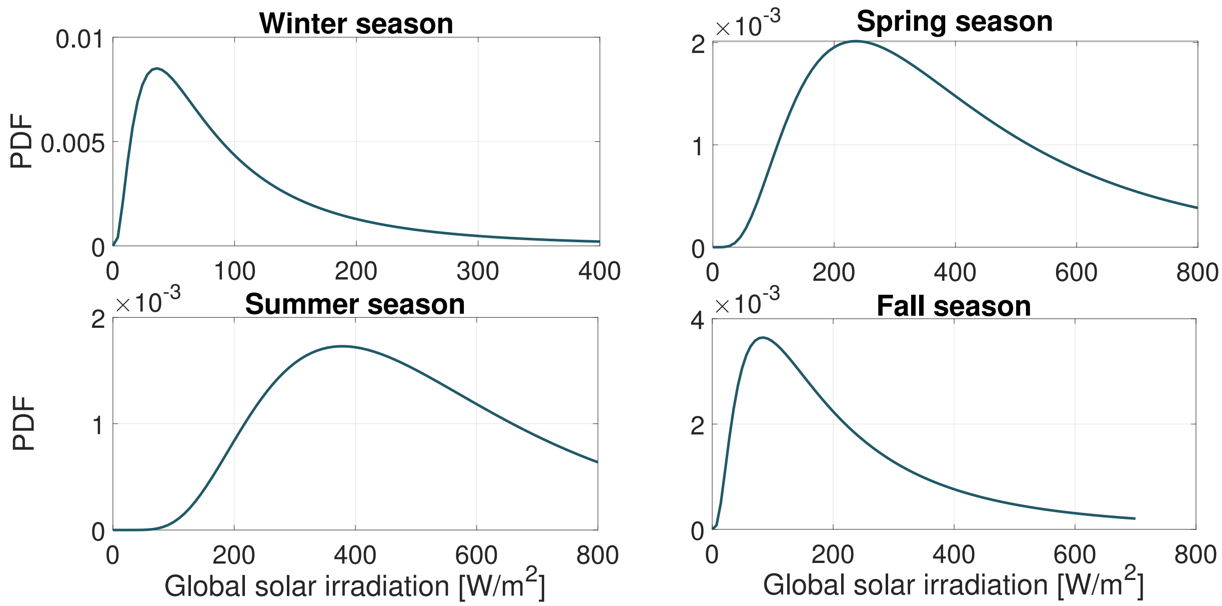


Figure B-10.: Log-normal PDF for the global solar irradiance in a typical seasonal day at 12:00h

for simulations are presented below. The data can be digitally consulted in (Contreras *et al.*, 2020a).

B.3.1. Components and economical data

The data regarding the planning components and economical data can be digitally consulted in (Contreras *et al.*, 2020a). A summary of some of the data is presented in Table **B-1**

Table B-1.: General techno-economic parameters for DERs

Objective function	**Symbol**	**Units**	**Technologies**			
			MT	WT	PV	BA
Turnkey capital cost of technologies	C_{CCD}	[\$/kW]	2668	1477	–	–
Fixed capital cost of technologies	C_{FCC}	[\$/kW]	–	–	1388	650
Variable capital cost of technologies	C_{OMV}	[\$/kWh]	0,0	0,0	0,0	0,0
Variable annual O&M costs	C_{OMV}	[\$/kWh]	0,0040	0,0100	0,0	0,0
Fixed annual O&M costs of technologies	C_{OMF}	[\$/kW]	8,3750	4,1660	0,25	0,25
Expected lifetime of technology	L_t	[Years]	20	10	30	5
Annuity factor for investments in technologies	A_n	[–]	0,08002	0,1295	0,0651	0,2310

Clearing prices in the PJM market

The clearing prices for the AS provision in the PJM market and energy export to the wholesale market are presented in Figures **B-11**-**B-14**.

Clearing prices in the CAISO market

The clearing prices for the AS provision in the PJM market and energy export to the wholesale market are presented in Figures **B-17**-**B-20**

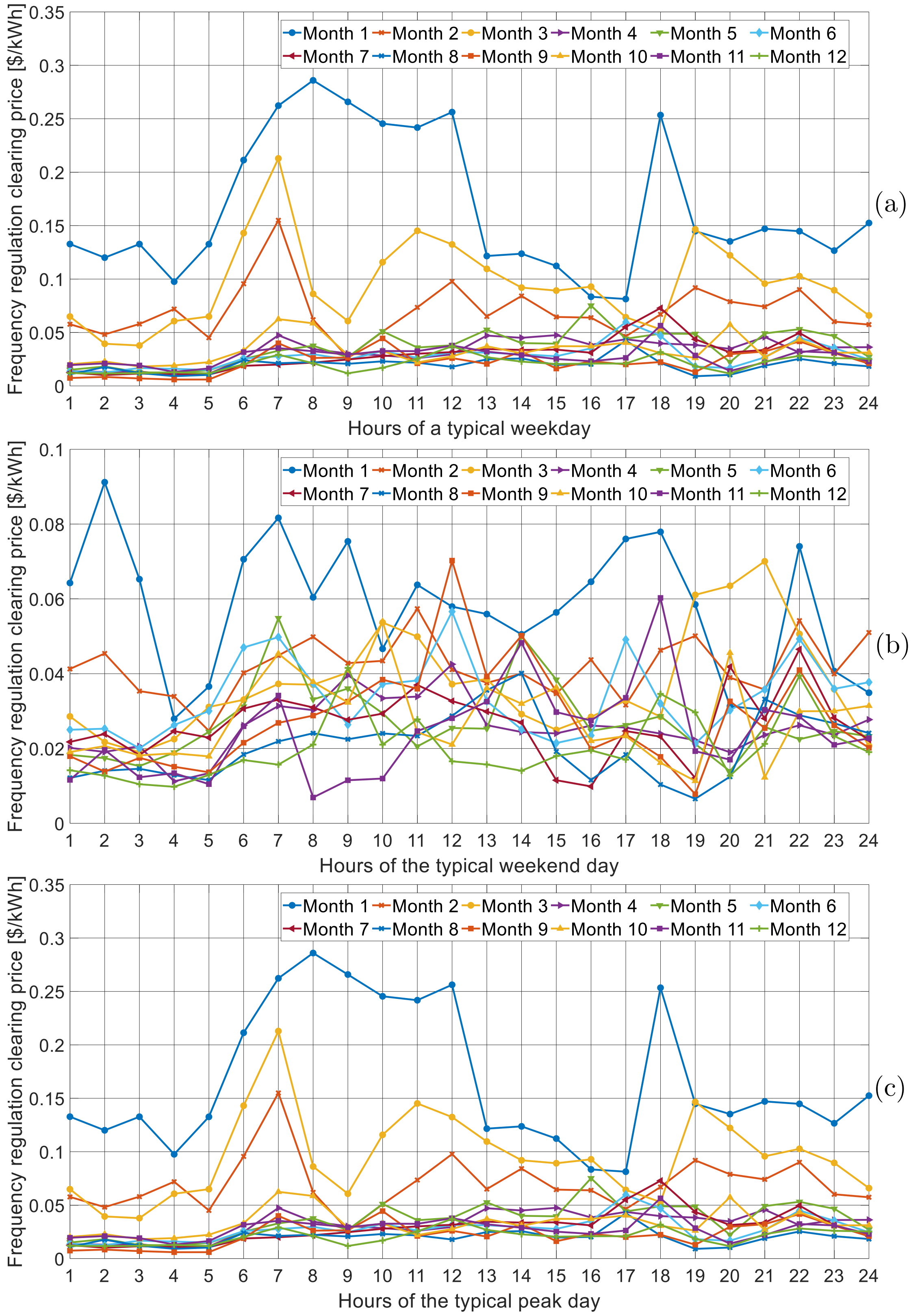


Figure B-11.: PJM average clearing price for the frequency regulation AS. a) Weekday, b) Weekend, c) Peak day

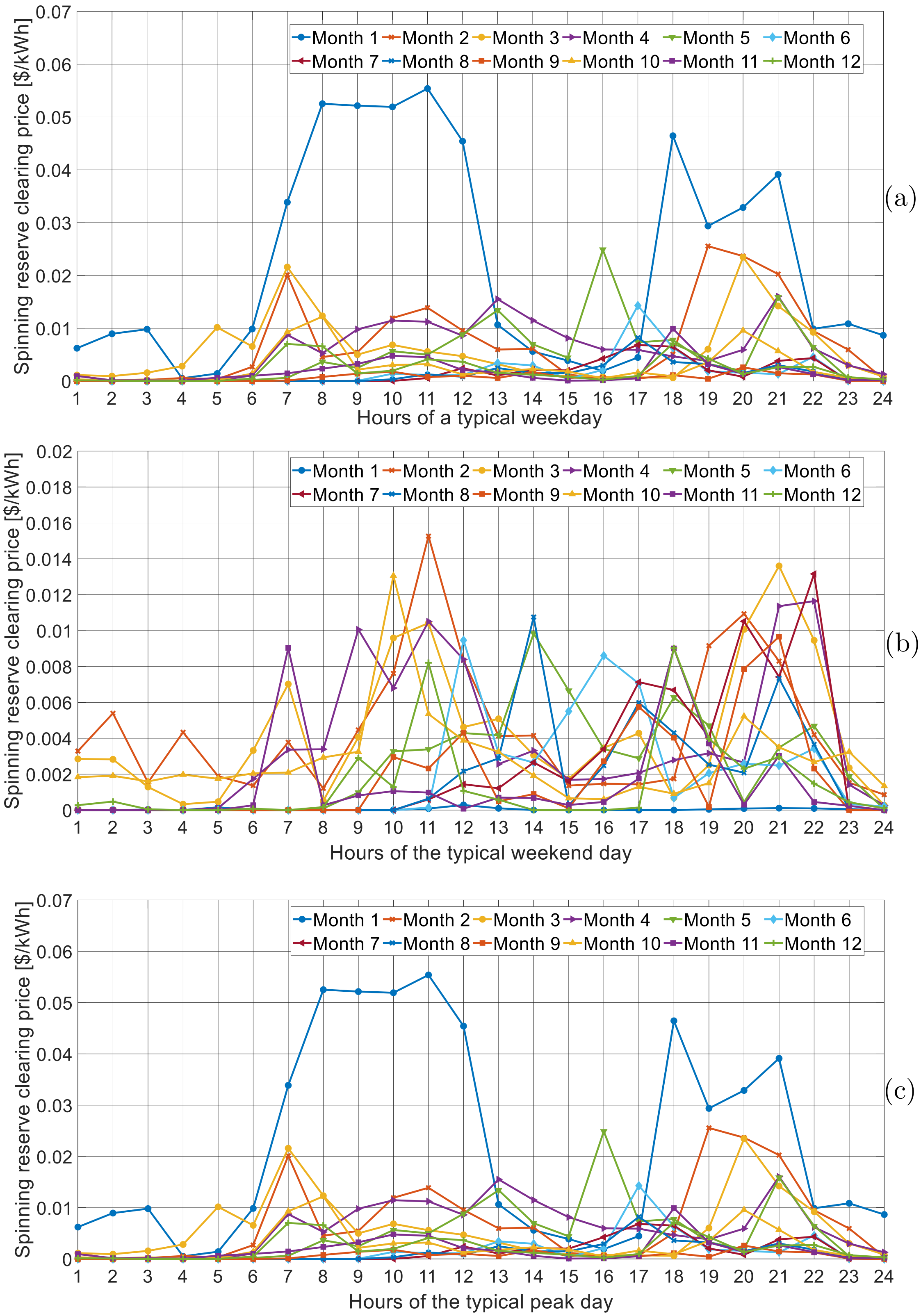


Figure B-12.: PJM average clearing price for the spinning reserve AS. a) Weekday, b) Weekend, c) Peak day

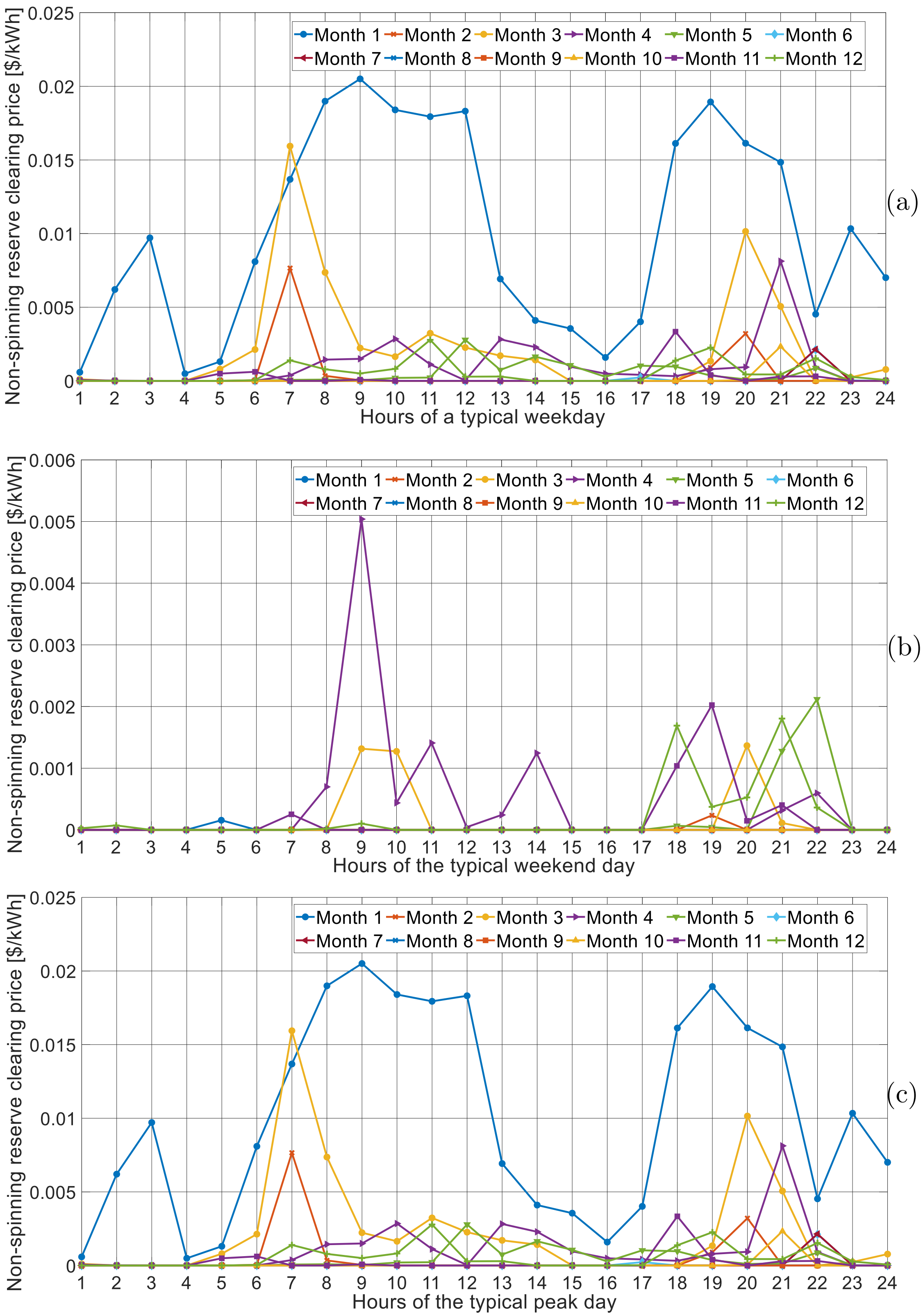


Figure B-13.: PJM average clearing price for the non-spinning reserve AS. a) Weekday, b) Weekend, c) Peak day

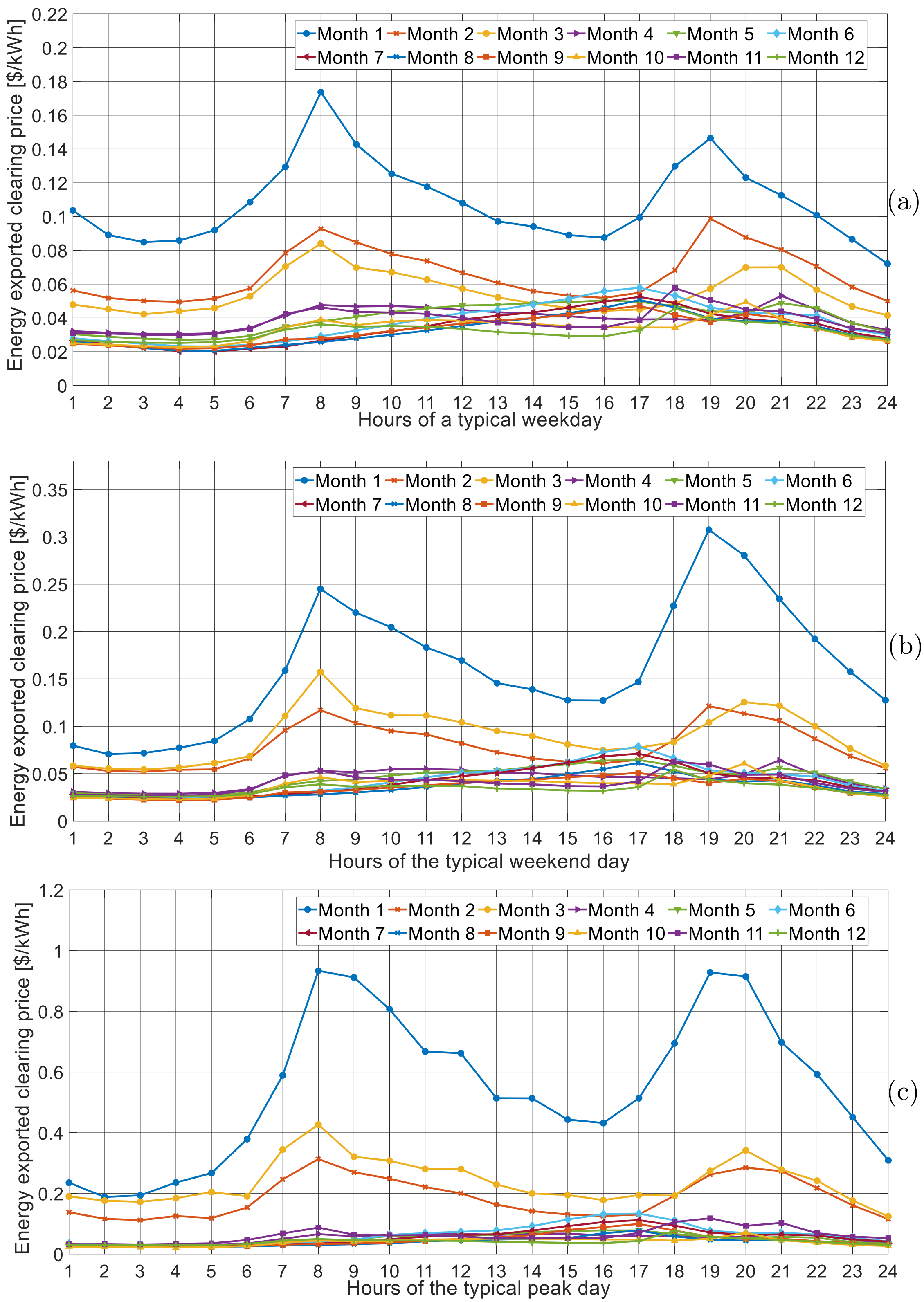


Figure B-14.: PJM average clearing price for energy export to the wholesale market. a) Weekday, b) Weekend, c) Peak day

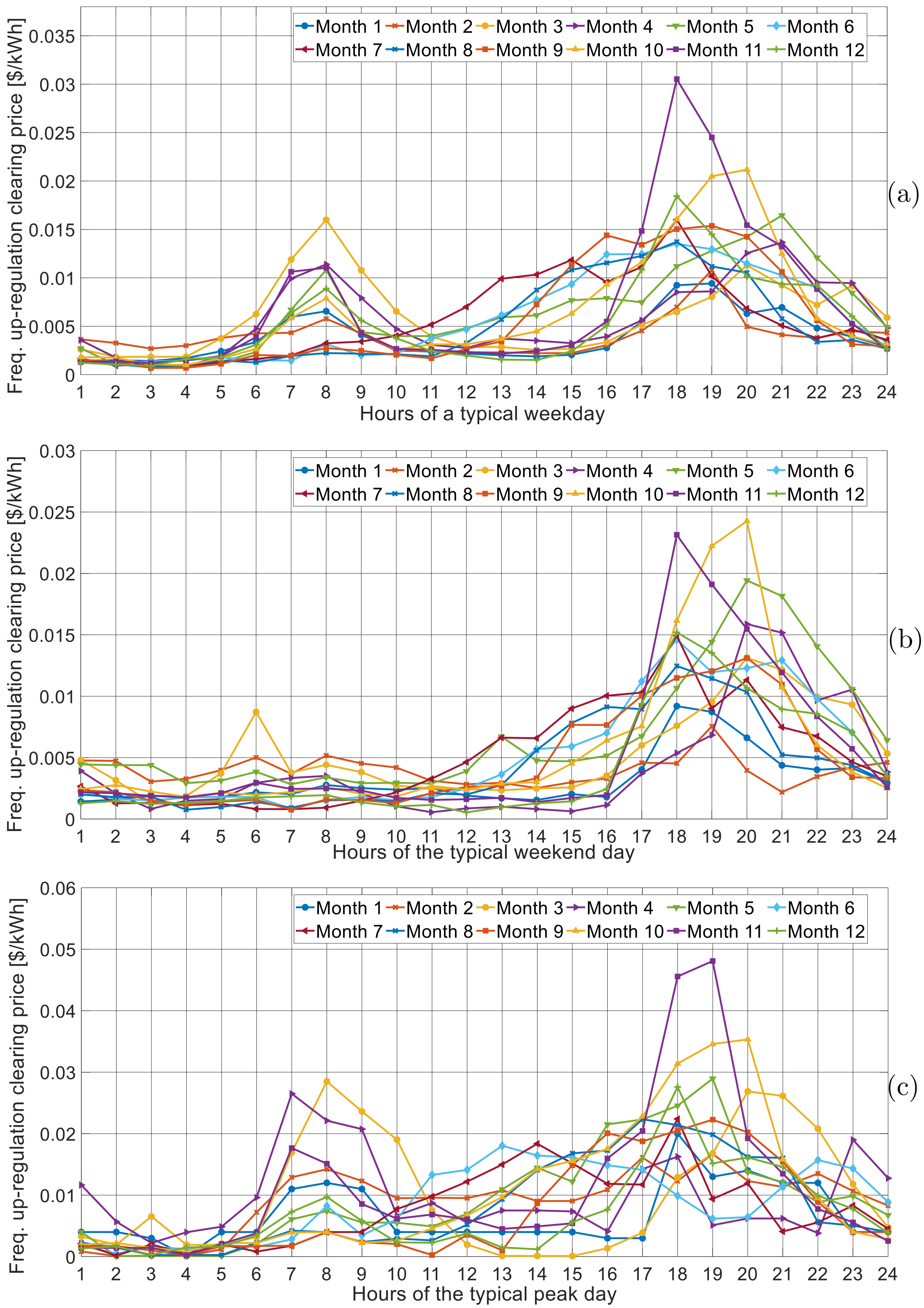


Figure B-15.: CAISO average clearing price for the frequency up-regulation AS. a) Weekday, b) Weekend, c) Peak day

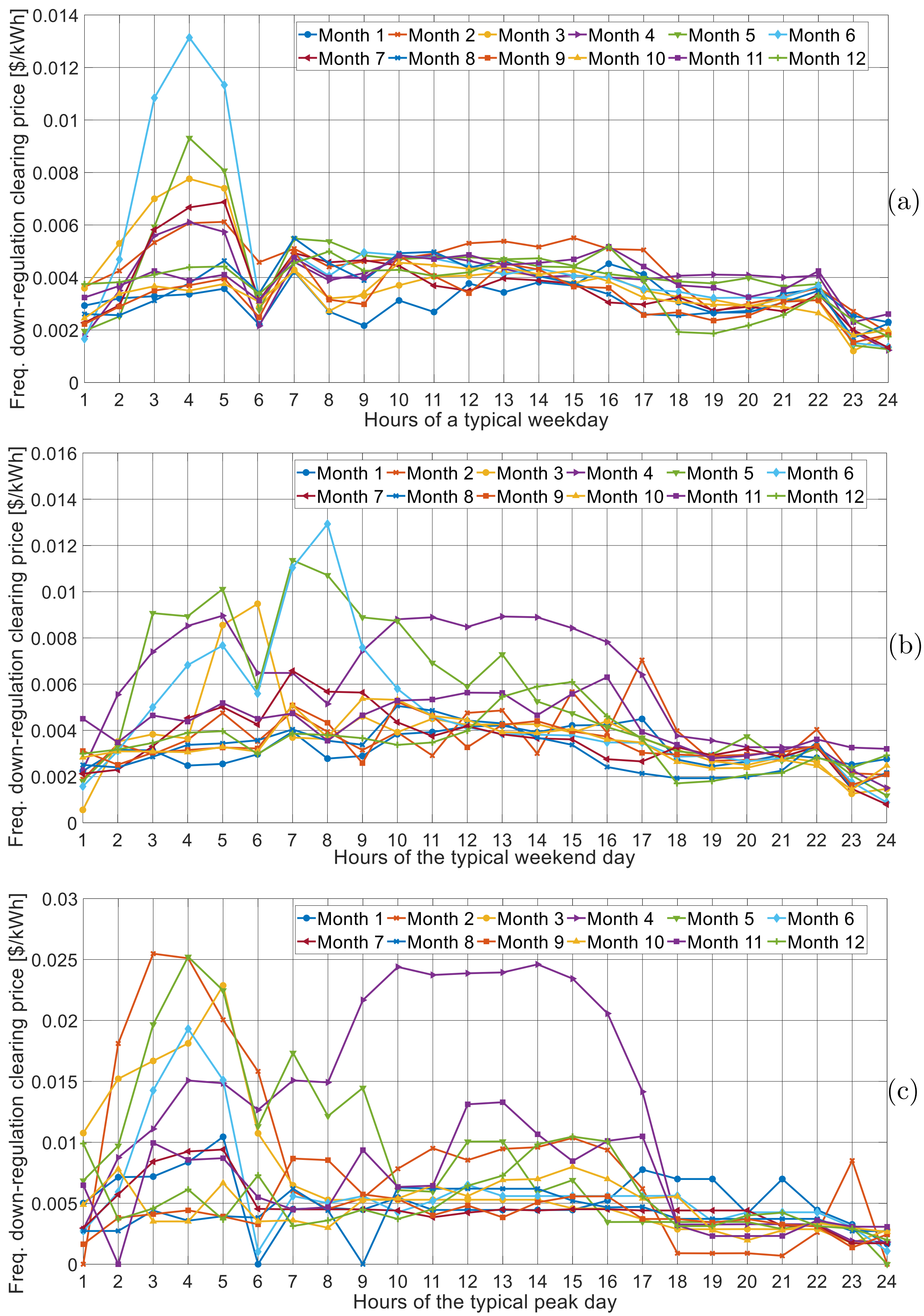


Figure B-16.: CAISO average clearing price for the frequency down-regulation AS. a) Weekday, b) Weekend, c) Peak day

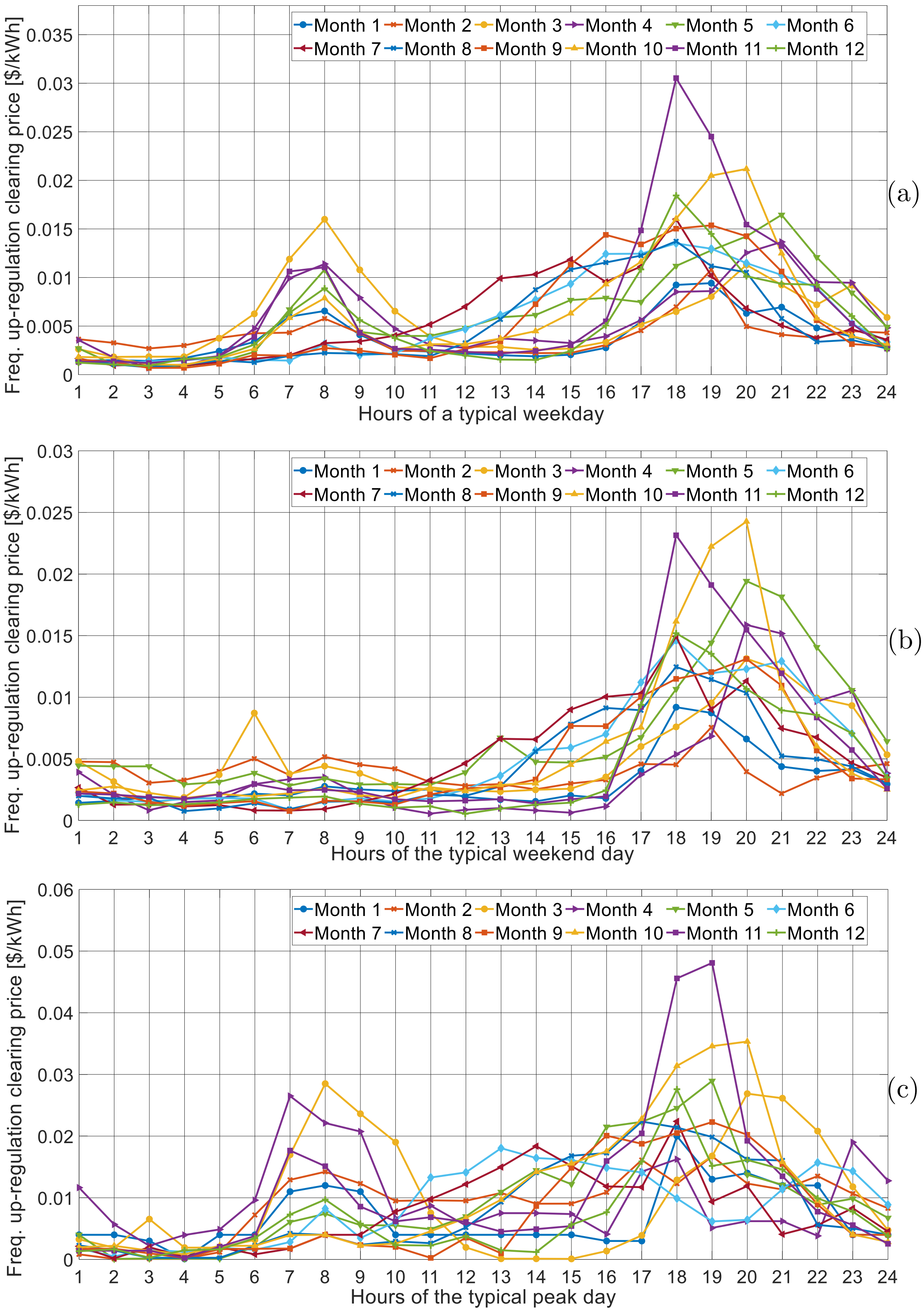


Figure B-17.: CAISO average clearing price for the frequency regulation AS. a) Weekday, b) Weekend, c) Peak day

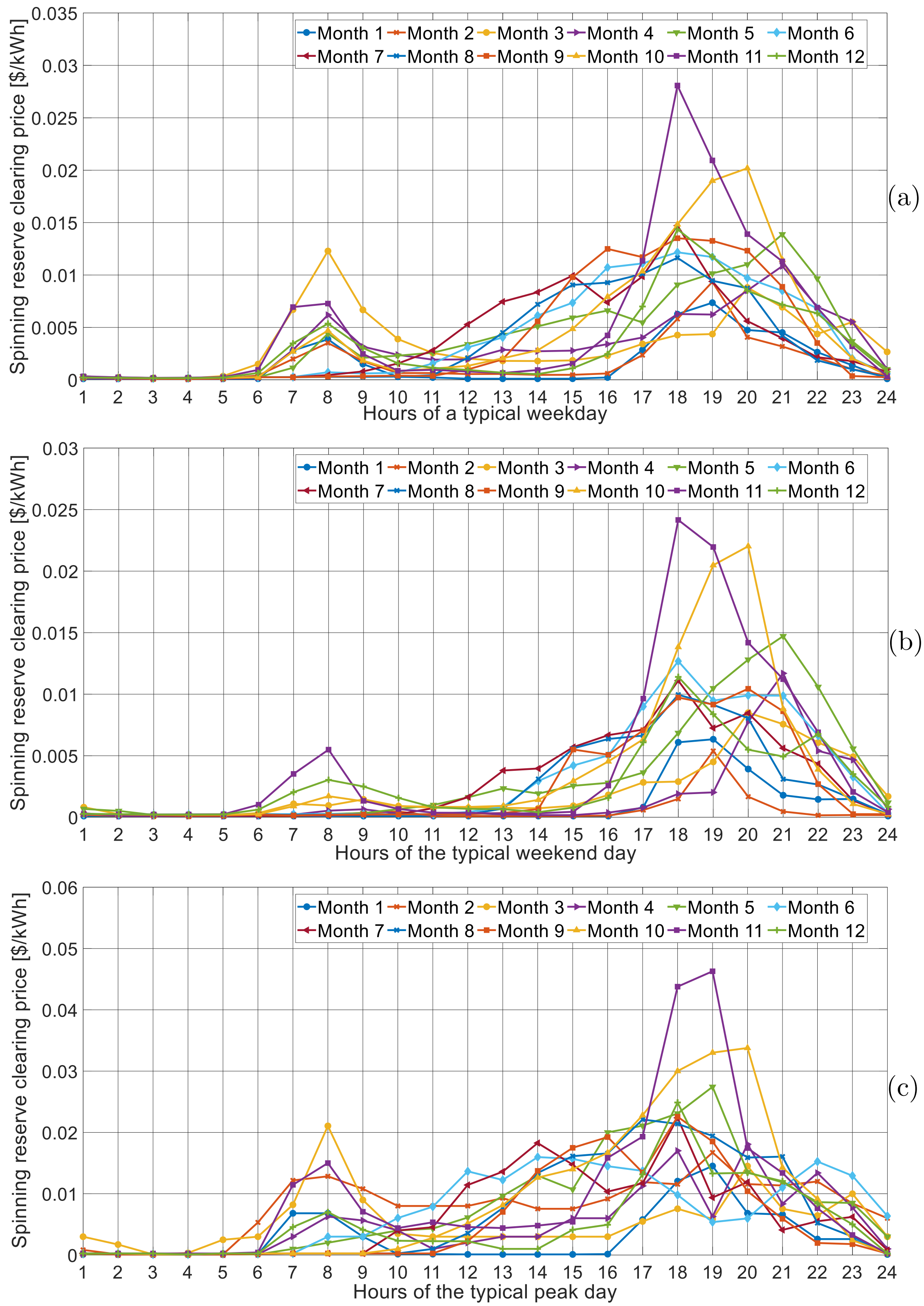


Figure B-18.: CAISO average clearing price for the spinning reserve AS. a) Weekday, b) Weekend, c) Peak day

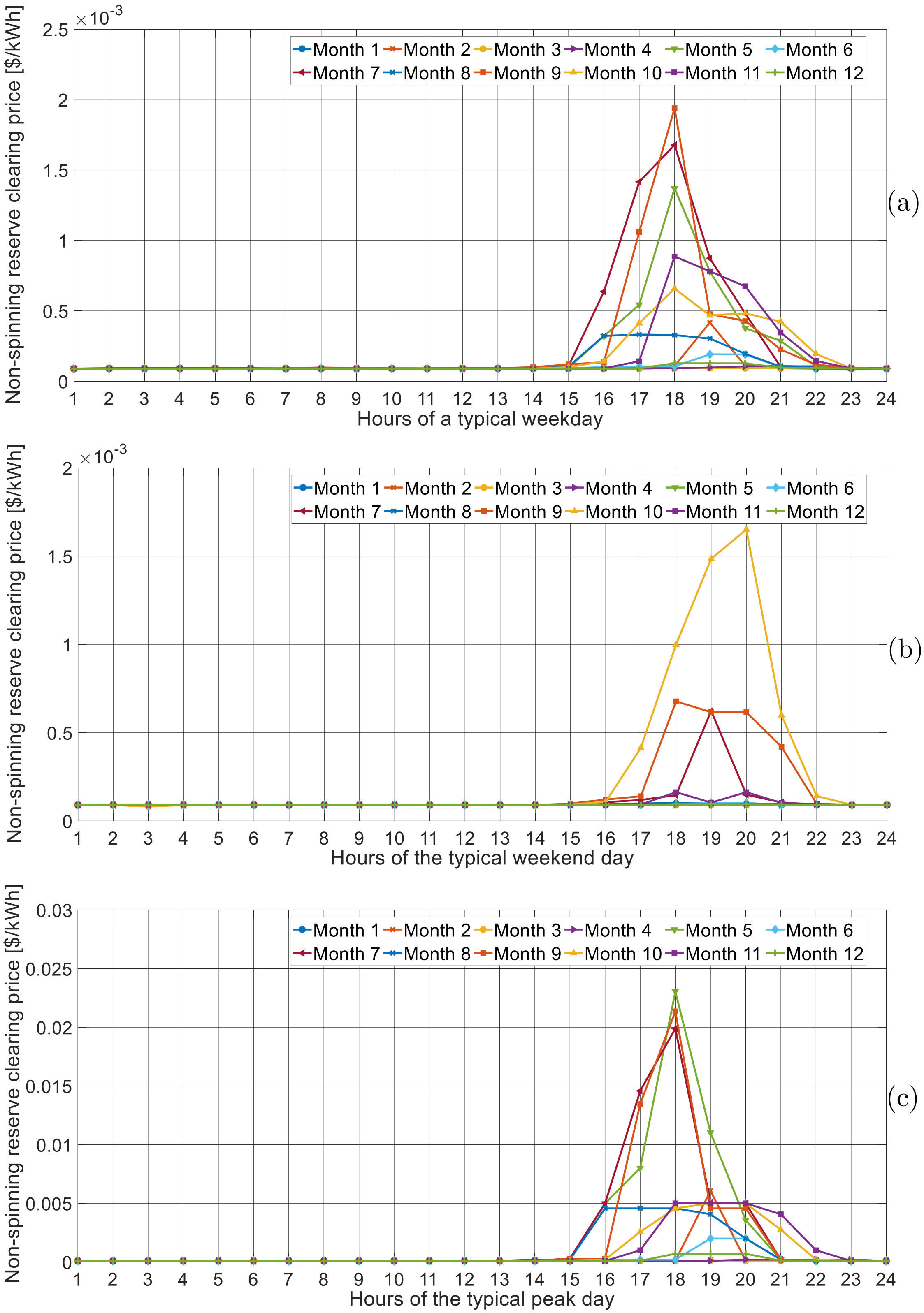


Figure B-19.: CAISO average clearing price for the non-spinning reserve AS. a) Weekday, b) Weekend, c) Peak day

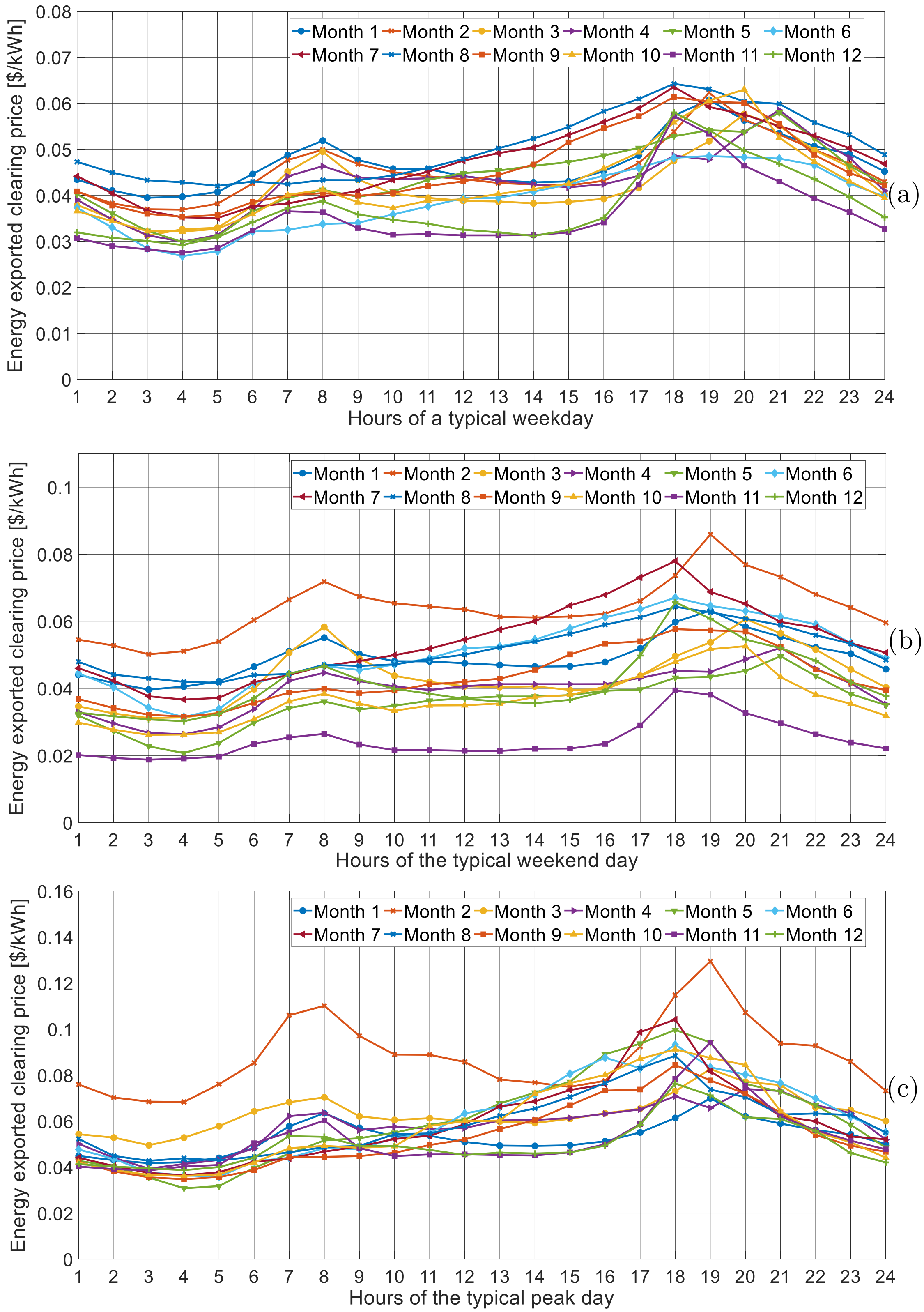


Figure B-20.: CAISO average clearing price for energy export to the wholesale market. a) Weekday, b) Weekend, c) Peak day

C. Appendix: Description of a Utility Microgrid benchmark

There are different benchmark of microgrids. In this appendix, a general description of an utility microgrid benchmark will be presented in order to offer a wider view of the context context and application scope for the POMMP and POMMP2 methodologies. Utility microgrids are also known in literature as community microgrid or simply milligrids, and are mainly differenciated from other type of microgrids because involves a part of the regulated grid. For this reason, CIGRE WG C6.22 (2015a) differentiates utility microgrids from conventional microgrids mainly from a regulatory and business model perspective instead of a technical point of view.

In the sections bellow, a benchmark from (Farhangi and Joos, 2019; Hatziargyriou *et al.*, 2007) is detailed and a list of utility microgrid examples are presented.

C.1. Example of a utility microgrid benchmark

As examples of current benchmarks of utility microgrid, the Boston Bar Hydro Project from the electric utility BC Hydro and the Distribution Test Line at Hydro-Québec in Canada were chosen. For that purpose, the information in (Bayindir *et al.*, 2015; Hatziargyriou *et al.*, 2007; Lidula and Rajapakse, 2011) was used to the first example, and (Farhangi and Joos, 2019; Ross *et al.*, 2014) for the second.

C.1.1. BC Hydro Boston Bar Microgrid

The BC Hydro Boston Bar is a MV microgrid of three radial feeders that interconnect a 69kV network with a 25kV distribution network. Therefore a normally connected 69kV/25kV substation operates as a the PCC. The microgrid was planned to reduce the effect of the power outages between 12 and 20h periods because of failures in the 65kV line. The microgrid comprises two 4,32MVA run-of-river hydro power generators connected to one feeder. The peak load of the microgrid is 3MW and has the capacity of operating and load managing in islanded mode. The single-line diagram can be seen in Figure **C-1**.

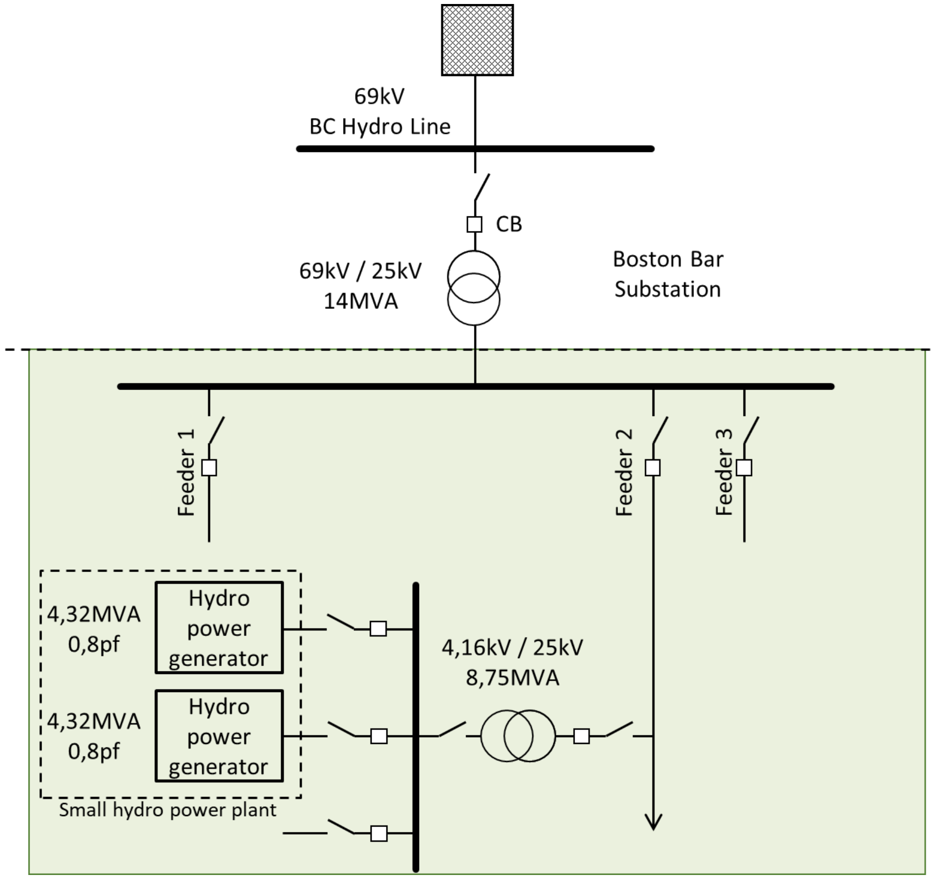


Figure C-1.: Single-line diagram of the BC Hydro Boston Bar Microgrid

C.1.2. Hydro-Québec Distribution Test Line Microgrid

The utility microgrid is composed by a three-phase 25kV overhead line that is fed from a 120kV/25kV, 28MVA $Y - \Delta$ substation transformer, grounded using a zig-zag transformer. The line is connected to several common elements that compose a typical distribution network such as circuit breakers, voltage regulators, shunt capacitor banks, protective switchgear, series reactance and potential and current transformers. Three overhead feeders and one underground feeder, to aloud topology reconfiguration, are connected to the input feeder. Three single-phase 14,4kV/347V, 167kVA transformers are used to connect the DERs to the Line 1 or 2. The single-line diagram of this utility microgrid benchmark is shown in Figure C-2.

The utility microgrid comprises the subsystems below:

- 400kVA diesel generator
- 200kVA induction generator. It is used to emulate a wind turbine generator.
- 300kVA synchronous generator.

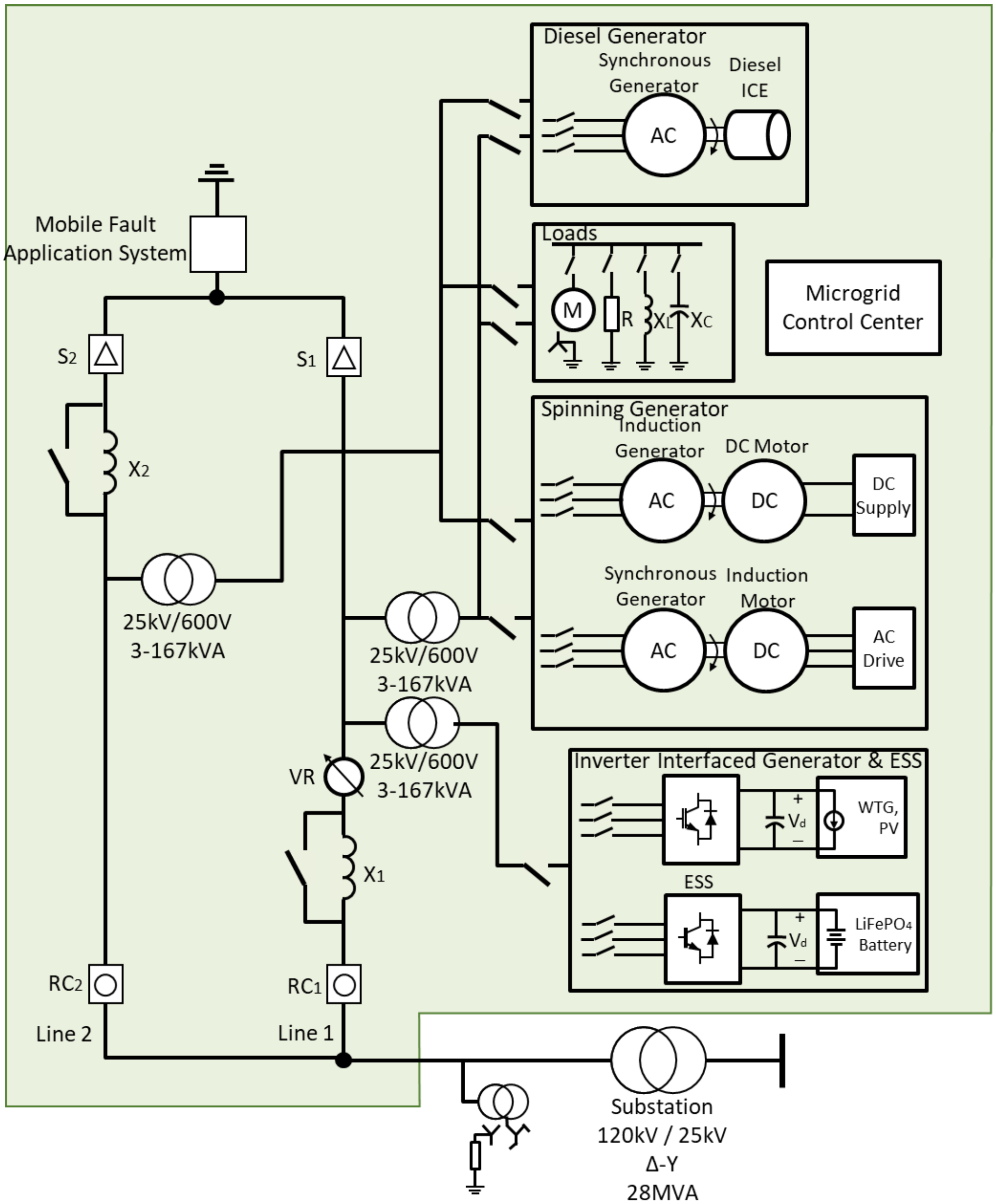


Figure C-2.: Single-line diagram of the Hydro-Québec Distribution Test Line Microgrid

- 250kVA inverter-based generator. It is used to emulate inverter-interfaced DGs, such as microturbines, wind and PVs.
- 100kWh, 200kVA energy storage system. It is a 100kWh Li-Ion battery system interfaced with a 250kVA bi-directional converter.
- 300kW, ±150kVAR controllable load.

- 600kW, load.
- 125HP induction motor load.
- Generic DER controller capable of PQ and/or PV control.

C.2. Compendium of international utility microgrid projects

CIGRE WG C6.22 (2015a), Obara and Morel (2017)[Chapters 8-10], Martin-Martínez *et al.* (2016), Bayindir *et al.* (2015) and Kroposki *et al.* (2008) describe practical utility microgrid projects in Europe, the Unite States and developing countries. A summary of them is summary in Table **C-1**.

Table C-1.: Examples of utility microgrid projects in the world

Project name	**Project Leader**	**Description and Characteristics**	**Technologies**	**Total (load) Capacity and type**
Allegheny Power (RDSI)	Allegheny Power (USA)	The microgrid has Wireless communications and dznamic configuration capabilities. It has a coordinated control of DER and can operate in grid-connected mode.	Biodiesel Engine, Microturbine, PV and ESS	2,1MW Total aprox.
Bornholm island Multi-Microgrid	MORE Microgrids (Denmark)	The transition between grid-connected mode to/from island mode were demostrated, as well as forecastign functions for generation and load. It has a coordinated control of DER and can operate in grid-connected and islande modes	Oil, Coal, Diesel, WTG, CHP, WT	39 MW Diesel + 39MW Steam (Oil) + 37 MW Steam (Coal/Oil) CHP + 30MW WT (55MWb peak)
Borrego Springs	SDG&E (USA)	The aim of the microgrid is to provide a proof-of-concept test about how information technologies and DERS can increase utility asset utilization and reliability.	ESS, PV, CES, HAN,	500 kW 3hrs Battery storage + 3-50kWh CES + 6-4kW/8kWh Storage + 700kW PV + 150 HAM (4MW)
Bostom Bar Hydro Project	BC Hydro (Canada)	The microgrid has the purpose of reducing outages by allowing islanding in a small community. It has a coordinated control of DER and can operate in grid-connected and islande modes	River Hydro	2x 3,45MW (8,6 MVA) KHP (3,0 MW peak)

Project name	**Project Leader**	**Description and Characteristics**	**Technologies**	**Total (load) Capacity and type**
Consolidated Edison (RDSI)	Consolidated Edison (USA)	It can be insulated and has dynamic configuration and fault insulation capabilities. It has a coordinated control of DER and can operate in grid-connected and islande modes.	Fuell Cells, demand response and PHEV	
Golden, BC-Energy Storage and Demand Response for Near-capacity Substation	BC Hydro (Canada)	The microgrid tests the integration of energy storage as a strategy to reduce electricity demand at near-peak capacity substations. It can operate in grid-connected and islande modes	ESS	3 x 1 MW ESS (30 MW aprox)
Mannheim - Wallstadt	MODE Microgrids (Germany)	The microgrid has the aim to optimize the power flow and power quality in parts of the microgrid in grid-connected mode. Furthermore, load controllers were installed and tested, as well as the concept of descentraliyed control with agents was tested. The islanding option and the control strategies were evaluated to improve the security of supply. Finally an iterative transition between grid-connected to islanded mode was demostrated. It has a coordinated control of DER and can operate in grid-connected and islande modes	PV, CHP, ESS	40kWe (480 Hauses)
Sacramento Municipal Utility District Microgrid (RDSI)	Sacramento Municipal Utility District (USA)	The microgrid has the purpose of demostrating the CERTS concept and test battery systems as well as management products. It has a CERTS Microgrid controller. It has a coordinated control of DER and can operate in grid-connected and islande modes.	PV, Fuell Cells and Microturbine CHP	3x100 kW Microturbine CHP+ 10kW PV+ 500kW Zn-Br Flow Battery (310 kW)
Tainjin Ecocity	Tainjin (China)			