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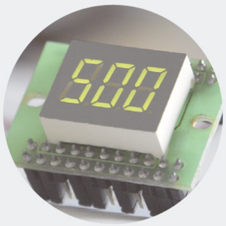

Optimal Planning of a Medium Voltage Distribution Network considering Uncertainty and Remuneration of Distributed Resources

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POLITÉCNICO
DO PORTO

OPTIMAL PLANNING OF A MEDIUM VOLTAGE DISTRIBUTION NETWORK CONSIDERING UNCERTAINTY AND REMUNERATION OF DISTRIBUTED RESOURCES

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Thanks

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Resumo

A prevalência de fontes de energia renovável nas redes elétricas tem crescido exponencialmente nos últimos anos. No entanto, esta transição também apresenta novos desafios para o planeamento das redes devido à natureza intermitente e imprevisível da produção de energia renovável.

Para lidar com estes desafios, este estudo introduz uma metodologia estocástica que permite que as redes façam investimentos informados em novas linhas e sistemas de armazenamento de energia. Focando numa rede de 180 barramentos em Portugal, a pesquisa utiliza uma abordagem estocástica de duas etapas que considera o impacto sazonal e a alta penetração de fontes de energia renovável. Fatores como a localização e o tipo de linhas de energia, e o tamanho e a disposição dos sistemas de armazenamento de energia são considerados.

A incerteza na produção eólica e solar, bem como nos dados de carga, é destacada na pesquisa, variando de acordo com as estações do ano e os períodos diários. Ao incorporar a incerteza e ao utilizar análise de risco condicional, o modelo fornece uma compreensão abrangente da dinâmica da rede. Os resultados demonstram o interesse económico da abordagem proposta, mesmo em eventos extremos, com reduções potenciais de custos de até 34%. Além disso, o modelo visa minimizar os valores de CO_2 e considera a remuneração dos geradores distribuídos, que muitas vezes é negligenciada no planeamento da rede.

O estudo incorpora 42 parques eólicos, 33 parques fotovoltaicos, três geradores de biomassa, uma subestação e sistemas de armazenamento de energia existentes. Ele garante uma remuneração justa para os participantes, enquanto minimiza os custos de planeamento, emissões de carbono e investimentos. O modelo proposto considera os impactos das estações do ano, incerteza e emissões de CO_2, fornecendo *insights* para o planeamento de redes em distribuição de energia renovável. Esta pesquisa oferece uma estrutura abrangente para um futuro mais limpo e sustentável, combinando incertezas, armazenamento, remuneração de recursos distribuídos, análise de risco condicional e emissões de carbono.

Palavras-Chave

Emissões de Carbono; Impactos Sazonais; Incerteza; Planeamento Ótimo; Redes de Distribuição; Remuneração; Sistemas de Armazenamento; Valor Condicional em Risco.

Abstract

The prevalence of renewable energy sources in power networks has grown exponentially in recent years. However, this transition also poses new challenges for network planning due to the intermittent and unpredictable nature of renewable energy output.

To address these challenges, this study introduces a stochastic methodology that enables networks to make informed investments in new lines and energy storage systems. Focusing on a 180-bus network in Portugal, the research employs a two-stage stochastic approach that considers seasonal impact and the high penetration of renewable energy sources. Factors such as the location and type of power lines, as well as the size and placement of energy storage systems, are considered.

Uncertainty in wind and solar generation, as well as load data, is highlighted in the research, varying according to seasons and daily periods. By incorporating uncertainty and employing conditional value-at-risk analysis, the model provides a comprehensive understanding of the network's dynamics. The results demonstrate the economic appeal of the proposed approach, even under extreme events, with potential cost reductions of up to 34%. Additionally, the model aims to minimize CO_2 values and considers the remuneration of distributed generators, which is often overlooked in network planning.

The study incorporates 42 wind farms, 33 photovoltaic parks, three biomass generators, one substation, and existing energy storage systems. It ensures fair remuneration for participants while minimizing planning costs, carbon emissions, and investments. The proposed model considers the impacts of seasons, uncertainty, and CO_2 emissions, providing valuable insights for network planning in renewable energy-rich distribution networks. Optimal planning models must adapt to address the challenges posed by the intermittent and unpredictable nature of renewable energy sources. This research offers a comprehensive framework for a cleaner and more sustainable future, combining uncertainties, storage, distributed resource remuneration, conditional value-at-risk analysis, and carbon emissions.

Keywords

Carbon Emissions; Conditional Value-at-Risk; Distribution Networks; Energy Storage Systems; Optimal Planning; Remuneration; Seasonal Impacts; Uncertainty.

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Acronyms

AAB	–	Annual Arbitrage Benefit
AGV	–	Aspremont-Gerard-Varet
AMPL	–	A Mathematical Programming Language
BCSSO	–	Binary Chaotic Shark Smell Optimization
CAES	–	Compressed Air Energy Storage
CO_2	–	Carbon Dioxide
CVaR	–	Conditional Value-at-Risk
DER	–	Distributed Energy Resources
DG	–	Distributed Generation
DLMP	–	Distribution Local Marginal Pricing
DN	–	Distribution Network
DNO	–	Distribution Network Operator
DR	–	Demand Response
DRO	–	Distributionally Robust Optimization
DSO	–	Distribution System Operator
EDS	–	Electrical Distribution Systems
EENS	–	Expected Energy Not Supplied
ERM	–	Energy Resource Management
ESS	–	Energy Storage Systems

EU	–	European Union
EV	–	Electric Vehicles
FOR	–	Forced Outage Rates
GECAD	–	Grupo de Investigação em Engenharia e Computação Inteligente para a Inovação e o Desenvolvimento
GEP	–	Generation Expansion Planning
HESS	–	Hybrid Energy Storage Systems
HFC	–	Hydrogen-Fuel Cell
HVAC	–	Heating, Ventilation, and Air Conditioning
IRR	–	Internal Rate of Return
KKT	–	Karush-Kuhn-Tucker
LARIMA	–	Long-term Autoregressive Integrated Moving Average
LC	–	Load Curtailment
MCDA	–	Multi-Criteria Decision-Making Analysis
MEPDN	–	Microgrid Energy Planning and Dispatch with Network Constraints
MILP	–	Mixed-Integer Linear Programming
MINLP	–	Mixed-Integer Non-Linear Programming
MISOCP	–	Mixed-Integer Second-Order Cone Programming
MV	–	Medium Voltage
NPV	–	Net Present Value
O&M	–	Operation and Maintenance

OPF	–	Optimal Power Flow
PGC	–	Power Generation Curtailment
PSO	–	Particle Swarm Optimization
PV	–	Photovoltaic
RAM	–	Random Access Memory
SAIDI	–	System Average Interruption Duration Index
SAIFI	–	System Average Interruption Frequency Index
SG	–	Smart Grid
SP	–	Scenario Probability
SQP	–	Sequential Quadratic Programming
VaR	–	Value-at-Risk
WPG	–	Wind Power Generation
WT	–	Wind Turbines

Nomenclature

Indices and Sets

bio	Biomasses
bs	Substation
c	Line options
e	Energy storage systems (ESS)
g	Distributed generators (pv+w)
i,j	Electrical buses
lo	Loads
pv	Photovoltaic parks
s	Scenarios
u	Energy storage system options
v	Electric vehicle parking lot (EVP)
w	Wind farms
Ω_B	Set of buses
Ω_{Bio}^b	Set of biomasses buses
Ω_{DG}	Set of dispatchable DG
Ω_{DG}^{nd}	Set of non-dispatchable DG
Ω_E	Set of ESS
Ω_L^b	Set of load buses
Ω_l	Set of lines
Ω_{PV}^b	Set of PV parks buses
Ω_s	Set of scenarios
Ω_v^b	Set of EVP buses
Ω_W^b	Set of wind farm Buses

Parameters

α	Confidence level
$\alpha_{PercPos}$	Alpha percentile position
β	Risk aversion
$\lambda_{(i,j,c)}$	Failure rate between lines *i* and *j* (failures/year)
$\lambda p_{(i)}$	Sum of all lines' failure rates (viewed from i)
ω_s	Scenario, s, probability
Bio_{Price}	Biomass generation price (m.u./MWh)
cef	Charge efficiency of ESS (%)
CutCost	Load curtailment cost (m.u./MWh)
def	Discharge efficiency of ESS (%)
EC_{CO_2}	Emission cost of carbon / Social cost of carbon (m.u./ton)
ENSCost	Energy not supplied price (m.u./MWh)
$FlowMax_{(i,j,c)}$	Maximum flow permitted from bus *i* to *j* (MW)
$FOR_{(i,j,c)}$	Forced outage rate between bus *i* and *j*
LineCost	Initial line investment (m.u.)
LineMCost	Line maintenance cost (m.u.)
$LF_{(i,j,c)}$	Loss factor between bus *i* and *j*
LossC	Power loss costs (m.u./MWh)
n	Project lifetime (years)
$N_{(i)}$	Consumers in bus *i*
nDG	Amount of DG units
Ns	Number of scenarios
$P_{ChargeLimit(v,s)}$	Limit of rate of charge of EV, *v*, in scenario, *s*
$P_{Load(lo,s)}$	Projected demand, *lo*, on scenario, *s* (MW)
PV_{Price}	Photovoltaic generation price (m.u./MWh)

r	Discount rate (%)
$r_{(i,j,c)}$	Repair time between bus *i* and *j* (hours)
$SAIDI^{max}$	Maximum SAIDI limit (h/consumer.year)
$SAIFI^{max}$	Maximum SAIFI limit (interruptions/consumer.year)
sf	Simultaneity factor
$stCap_{(e,u)}$	Capacity of ESS, *e* (MW)
$StCost$	ESS cost (m.u.)
$StMCost$	ESS maintenance cost (m.u.)
$St_{PriceInContract}$	Price for using ESS within contract limit (m.u.)
$St_{PriceOutOfContract}$	Price for using ESS out of contract limit (m.u.)
$stRate_{(e,u)}$	Rate of charge and discharge of ESS, *e* (%)
Sub_{Price}	Substation generation price (m.u./MWh)
ι_{Bio}	Emission rate of the biomass generators (ton/MWh)
ι_{bs}	Emission rate of the substation (ton/MWh)
ι_{E}	Emission rate of the energy storage systems (ton/MWh)
ι_{PV}	Emission rate of the photovoltaic parks (ton/MWh)
ι_{WI}	Emission rate of the wind farms (ton/MWh)
$Up_{(i)}$	Unavailability of all lines (viewed from bus *i*) (hours/year)
WI_{Price}	Wind generation price (m.u./MWh)

Variables

$a_{(e,u)}$	Binary variable for ESS, *e*, use
$CVaR$	Conditional value-at-risk
$d_{(i,j)}$	Made up flow from bus *i* to *j*
$D_{(g)}$	Made up load on each DG, *g*

$EVP_{(v,s)}$	Power charged in an EVP, in scenario *s* (MW)
$Flow_{(i,j,s)}$	Power flow between bus *i*, and *j*, in scenario *s* (MW)
$p_{Bio(bio,s)}$	Power generated by biomass, *bio*, in scenario, *s* (MW)
$P_{Charge(v,s)}$	Power charging of EVP, *v*, for scenario, *s*
$PCost_{PGC}$	Power generation curtailment cost (m.u./MWh)
$P_{DG(g,s)}$	Total DG, *g*, in scenario *s* (MW)
$P_{LoadCut(lo,s)}$	Power load curtailment in load, *lo*, scenario, *s* (MW)
$P_{PGC(g,s)}$	Power generation curtailment, for DG, *g*, in scenario, *s* (MW)
$p_{PV(pv,s)}$	Power generated by PV parks, *pv*, in scenario, *s* (MW)
$P_{storage(e,u,s)}$	Power charged/discharged in an ESS, *e*, in a scenario, *s*
$p_{Sub(s)}$	Power delivered by the substation in scenario, *s* (MW)
$p_{WI(wi,s)}$	Power generated by wind, *w*, in scenario, *s* (MW)
SAIDI	System Average Interruption Duration Index (h/consumer.year)
SAIFI	System Average Interruption Frequency Index (int/consumer. year)
t_c	Total cost of all combined scenarios (m.u.)
VaR	Value-at-risk

1. INTRODUCTION

The work carried out during this thesis is done as a collaboration with the GECAD research center and aims to optimally introduce uncertainty (seasonal variations, wind and photovoltaic (PV) generation, and load) and remuneration of distributed resources in planning models for Medium Voltage (MV) grids with a high percentage of RES (Renewable Energy Sources) penetration. Additionally, more objectives were implemented, namely the consideration for risk aversion through value-at-risk (VaR) and conditional value-at-risk (CVaR) and the consideration for minimizing CO_2 emissions.

This chapter aims to introduce the work briefly and contextualize it, as well as the main objectives planned for the work, and how the thesis is structured. Lastly, there is also a section regarding publications derived from this work.

1.1. CONTEXTUALIZATION

The studied topic was proposed by Professors Bruno Canizes and João Soares, aiming to optimally plan a distribution network (DN) on MV, with special consideration for seasonal uncertainties, remuneration of resources, risk aversion, and CO_2 emissions in several situations. This analysis derives from previously published work in [1] and aims to deepen the level of study by minimizing the possible effects considering this uncertainty by implementing Energy Storage Systems (ESSs) and other factors. The study was applied to a 180-bus network in Leiria District, Portugal. A two-stage stochastic model was be used to implement the proposed method, and 50 000 scenarios were created, which would then be reduced to a lower number using a scenario reduction tool, facilitating the study regarding computational resources and time. This work aims to fill some gaps in the current state-of-the-art by proposing advancements corresponding to a methodology to adequately intertwine most of modern network planning’s needs (uncertainty, ESSs, remuneration of resources, risk aversion, carbon emission control), with the main objective being creating common ground between all these topics since most current literature considers some of them, but not all simultaneously. As such, this thesis aims to answer the research question, “Can a multistage stochastic risk-based optimization considering RES remuneration, uncertainty, storage, and emission control be advantageous for long-term MV distribution network planning?".

A major reason to conduct this study is to enable the idea that all relevant topics must be considered in the optimization model, all while minimizing all possible associated costs. Most of the related literature to optimal planning falls short in terms of being faithful to a real-world scenario, despite how favorable they seem. This document aims to group relevant literature and then aims to propose a novel stochastic model to adequately merge all the topics mentioned above with relevant considerations for each.

Regardless of the stride this thesis aims to achieve, it can still consider some more elements, as is be shown later in the conclusions.

1.2. OBJECTIVES

The main goal of this work is to plan an optimal expansion of a medium voltage distribution network while minimizing all associated costs. For this, several objectives are defined:

- Characterization and parameterization of an MV electrical network with a high degree of distributed generation penetration;
- Creation and incorporation of the uncertainty of previously developed seasonal scenarios into the planning model;
- Considering every available resource in the distribution network (distributed generation, energy storage systems, electric vehicle), reliability, losses, new distributed generation, capacitor banks, and new lines in the same model;
- Including forms of remuneration for the owners of the distributed generation and energy storage systems, which must be effectively separated from the function of the distributed system operator;
- Test and validation of results through several simulations;
- Writing a scientific article, as well as the thesis.

Additionally, the following objectives were achieved, despite not being initially proposed:

- Considering the occurrence of extreme events, even if they have a low probability, and minimizing their potential issues through risk aversion (VaR and CVaR);
- Implementing a consideration for minimizing carbon emissions by applying an emission rate to every technology along with the emission costs (social cost of carbon).

1.3. THESIS STRUCTURE

This document is divided into five main chapters. The first chapter introduces the topic and lists the objectives the study aims to achieve. The second chapter explores the current state-of-the-art about optimal planning on DN, analyzing optimal planning in general, optimal planning with ESSs and no uncertainty, and the opposite, optimal planning with both uncertainty and ESSs, remuneration of RES, risk aversion, and carbon emission control. Chapter 3 aims to explain the methodology used, starting with the scenario creation and uncertainty application, followed by the considerations for the remuneration of Distributed Generation (DG), the CVaR and VaR specifications, and the carbon emission specifications. Following that, the full optimization model is shown (objective function, constraints, etc.), and, lastly, the explication of the approach to the economic analysis is shown, followed by the chapter conclusions. Chapter 4 outlines the case studies where the methodology is applied and then discusses the results after applying the proposed methodology to the studies. Lastly, chapter 5 shows a general conclusion to the work, presenting the main draws taken from the research.

1.4. PUBLICATIONS

As part of the development of this thesis, several scientific articles have been made, such as the following:

- Review paper titled “A Brief Review on Optimal Network Planning Considering Energy Storage Systems and Uncertainty”, by F. Castro, B. Canizes, J. Soares, and Z. Vale, International Conference on Future Energy Solutions (FES2023), which took place from the 12th to the 14th of June 2023. DOI: 10.1109/FES57669.2023.10182511 [2]; **(Published)**

- Paper titled "Hourly Uncertainty in Optimal Expansion Planning considering Energy Storage and Seasonal Impacts", by F. Castro, B. Canizes, J. Soares, and Z. Vale, IEEE PES ISGT Europe 2023 (ISGT Europe 2023). Conference is due to take place from the 23rd to the 26th of October 2023; **(Accepted for Publication)**

- Paper titled "Distributed Resources' Remuneration on a Medium Voltage Network with Uncertainty and Seasonal Impacts", by F. Castro, B. Canizes, J. Soares, M.J. Rider, and Z. Vale, Energy Informatics. Academy Conference 2023 (EI.A 2023). Conference is due to take place from the 6th to the 8th of December 2023; **(Accepted for Publication)**

- Paper titled "Risk-based Optimal Network Planning considering Resources Remuneration and Daily Uncertainty", by F. Castro, B. Canizes, J. Soares, J. Almeida, B. Francois, and Z. Vale; **(Under Review)**

- Paper titled "Optimizing Smart Distribution Network Expansion Incorporating the Seasonal Impacts, CO2 Emissions and Resources Remuneration: A Multi-Stage Stochastic Framework", by F. Castro, B. Canizes, J. Soares, J. Almeida, and Z. Vale, International Conference on Applied Energy 2023 (ICAE 2023). Conference is due to take place from the 3rd to the 7th of December 2023; **(Accepted for Publication)**

The following papers were also developed but not directly related to the thesis' topic:

- Paper titled "A Logic-Based Flexibility Services Tool to Support a Rich Renewable Distribution Network Operation", by B. Canizes, F. Castro, V. Silveira, and Z. Vale; **(Under Review)**

- Paper titled "Hybrid-Adaptive Differential Evolution with Iterated Local Search for Long-Term Transmission Network Expansion Planning Optimization", by J-Almeida, F. Lezama, J. Soares, B. Canizes, F. Castro, G. Puerta, L.H. Macedo, and Z. Vale, International Conference on Applied Energy 2023 (ICAE 2023), Conference is due to take place from the 3rd to the 7th of December 2023; **(Accepted for Publication)**

2. LITERATURE REVIEW

This chapter represents a review of the current state-of-the-art concerning optimal planning of networks, specifically focused on a situation of potential distribution grid expansion, considering RES, ESS, uncertainties, remuneration of resources, risk aversion, and carbon emissions. When considered relevant to the review, some literature that does not follow this structure was also studied.

It is known that the optimal planning of ESSs on a transportation network brings along a handful of environmental, economic, and flexibility benefits [3], [4]. Their inclusion is crucial in network planning, especially nowadays, with the strong need for better network flexibility. It is known that this transition to renewable generation sources is inevitable and essential as part of meeting the European Union's (EU) requirements of having 40% RES penetration by 2030 [5], and as it is known, brings along several challenges to the network that previously were not an issue. Introducing uncertainties and ESSs is one way of reaching precise results and mitigating the more prominent effects of RES. This chapter was divided into seven sections: General optimal planning of networks; Optimal planning of networks considering ESSs; Optimal planning of networks considering uncertainties; Optimal planning of networks considering both ESSs and uncertainties; Remuneration of distributed resources; Risk assessment on network planning; and CO_2 emissions.

2.1. GENERAL OPTIMAL NETWORK PLANNING

Optimal planning in electricity grids is essential and is becoming more and more prevalent as time goes on. In recent years, DG has been seen as a reliable alternative to the more traditional plan of simply expanding the network. An ever-emerging risk with today's electricity mix associated with accelerated load demand growth and high penetration of RES calls for meticulous and precise optimization regarding several factors associated with the distribution of energy [6]. The literature reviewed in Table 1 and discussed in the following analysis covers general grid planning. Still, it does not delve into uncertainty, ESSs, remuneration, risk, or carbon emissions, which is examined later in this document.

Table 1 - General optimal network planning literature

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[7]	Optimization of WT power factor	Reduction of power losses	Stochastic Model for WPG and load demand on a 69-bus grid	Does not consider uncertainties related to used data
[8]	SG Management	Cost reduction of energy delivery to consumers	A mathematical model to optimize the costs of generation of DG, primary substation, and grid power losses solved with SQP and a nonlinear programming solver	Does not consider the possible benefits of introducing ESS's
[9]	Optimal planning of network expansion	Minimize costs/emissions Optimal sizing and placement on DG units	A two-stage heuristic method is used, with the help of a genetic algorithm, which leads to an iterative methodology	Does not consider possible ESS's as well as any uncertainty; and the case where independent investors instead of DNO does the DG investment
[6]	Innovation on MEPDN	Minimize Investment and Operation Costs	A BCSSO method is used to approach this issue, as well as an analytical approach to minimize the EENS of distribution network based on the DGs' restoration	DG's uncertainty is not considered, although a future reevaluation of this issue is planned by the authors
[10]	Optimization model for Distribution planning	Minimization of investments, operation costs, and losses	Optimization model supported by binary variables applied to a number of different scenarios	Does not consider any uncertainty, as well as ESS's, although it is worth noting that ESS's were not as popular or established as of the release date
[11]	Multi-Objective Network Reconfiguration	Minimization of active power loss Maximization of	Multi optimization models considering soft open points based on NSGA – II with a	Only considers remodeling an already existing system, and is

Ref.	Focus	Main Objectives	Used Techniques	Limitations
		minimum voltage of the nodes	decision maker applied to a 33-bus system	not prepared to provide information about new lines, ESS's, types of lines, etc.

In reference [7], Chen et al. propose optimizing grid planning by reducing system power losses by controlling WT (Wind Turbine) power factors. All this is done through a stochastic model based on LARIMA (Long-term Autoregressive Integrated Moving Average) and is carried out on a 69-bus grid. The authors found that controlling the power factor has a pleasant effect on losses when compared to a unitary power factor. It is also demonstrated that WT owners must pay less through transaction fees.

Cecati et al. in [8] propose ways to optimize smart grids by minimizing total costs related to delivering energy to consumers, from DG generation costs to substation costs to power loss costs. The authors use a power flow algorithm and verify it on a real grid with wind and diesel generators.

In [9], a multi-objective planning model is presented for a DN with DG options, which optimizes costs and emissions and determines the optimal sizes, places, and dynamics of DG units and network reinforcements. The authors apply their two-step model to an already existing grid and compare it to benchmark methods to prove the effects of their work in action. The authors decided which buses would house which characteristics through a Pareto optimal front method, where they chose the bus that appeared the most in any studied scenario. Results were as shown in Fig. 1.

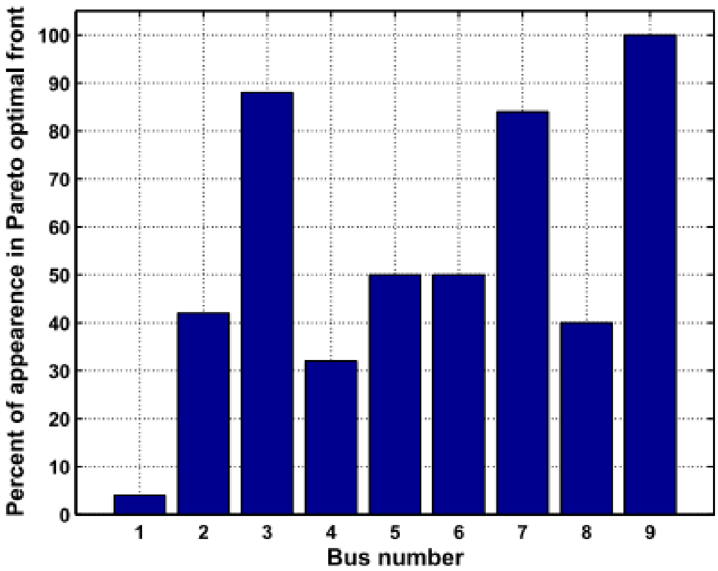

Figure 1 - Results for bus selection to house installments (Source:[9])

Ahmadigorji et al. in [6], propose a new model specifically for expanding networks in a multi-year period. This model aims to determine the scheme of the grid, including protection, and the location and size of DG. This model has the specification of being able to adjust the timeslot as well as investments freely, meaning that any value of "simulation" can be used. The main objective is, naturally, minimizing total costs, using a BCSSO (Binary Chaotic Shark Smell Optimization). After, the model is applied to two different networks, one with 12 and one with 33 buses. The authors compare their method to 11 other benchmark models and outperform them all.

As for [10], an optimization model for planning DG is made. The main objective is a common one being the size and allocation of DG on the network, while minimizing investment, operation, and loss costs, as well as possible new scenarios such as expanding or reconfiguring the network, such as new substations. The authors then compare their method to a deterministic approach and other benchmark options and find the best suitable solutions for a grid.

In [11], Dai proposes a network reconfiguration model with a soft open point based on NSGA-II with the Pareto front being generated by minimizing losses and voltage offset of DN, those two being two different objective functions in a two-step problem. Hence, the outcome is more feasible, according to the author. The model is applied to a 33-bus grid and compared to standard methods.

2.2. OPTIMAL NETWORK PLANNING CONSIDERING ENERGY STORAGE SYSTEMS

In recent years, the inclusion of energy storage systems in grids has become a staple center in optimal grid planning. The ever-increasing RES penetration level in the energy mix has seen the uprising of some issues that were not considered a problem beforehand, such as an inherent difficulty in controlling the flexibility of the grid and a major unavoidable difficulty in forecasting data related to electricity such as planning the balance between load and demand. Many authors have provided studies that support the fact that mainly wind, and solar generation have a direct correlation to forecasting errors, lower flexibility, and eventual spikes in electricity prices, which could go both ways and go as far as being negative [12], [13]. The consensual suggestion to a lot of literature surrounding the topic seems to be that measures need to be taken to solve or mitigate these issues, with the insertion of ESS as the preferred solution [14], [15]. In Table 2, the preferred storage methods in grids can be seen and in Fig. 4 there is a possible configuration of its inclusion on the grid.

Table 2 - Preferred forms of energy storage (Adapted from: [16], [17])

Forms of Storage	
1 – Air	2 - Batteries
3 – EVs	4 – Flywheel
5 - Hydrogen	6 – Hydroelectricity
7 – Superconducting magnets	8 - Thermal
9 – Gravitational potential energy storage with solid masses	

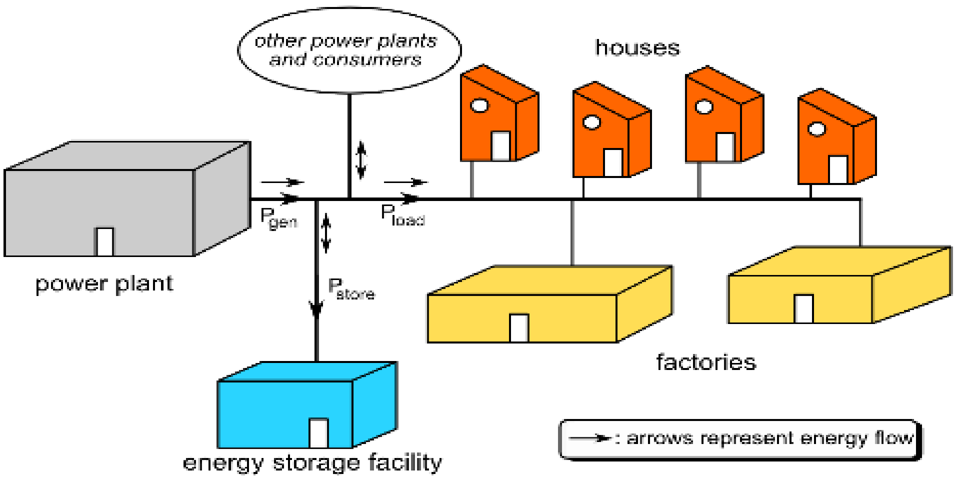

Figure 2 - Potential location of insertion of ESS (Source:[16])

Following on Table 3 is a brief summary of a set of literature that addresses different topics related to the input of energy systems on networks, such as their optimal size and location and the effects its insertion causes. This literature is then analyzed more carefully, and the associated conclusions are demonstrated.

Table 3 - Optimal network planning considering ESSs literature

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[18]	Expansion planning incorporating large scale ESS	Minimizing planning costs and environmental pollution	Mixed-integer nonlinear programming and PSO algorithm	Not considering the potential uncertainty of generation and demand when forecasting data
[19]	Optimization of active DN considering maximum DG	Maximizing DG value / Minimizing distribution costs	Day-ahead optimization model solved with Particle Swarm Optimization	Not analyzing optimal spot for ESS (pre-chosen node) and no uncertainty for any data used including RES
[20]	Effects of energy storage in grids	Understand how ESS impacts price forecasting, arbitrage limits, curtailment insurance, and transmission line use	Economy theory to quantify profit limits with addition of ESS and microeconomic models to link data	Not choosing type of ESS despite choosing optimal locations for them

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[21]	Planning of RES with ESS application	Analyze different combinations of RES and ESS to select the best future investments	Two-stage planning based on MCDA	Not applying certain characteristics (geographical, capacity, demand, environment)
[22]	Optimization and planning in presence of fluctuation and ESS	Explore different planning strategies to study how profitable they are with cogeneration	Mixed-integer quadratic-based multi-objective model	Does not approach the introduction of factors in a machine-learning way, only provides 3 cases

In reference [18], Hemmati et al. analyze how impactful the potential insertion of large-scale ESS in grids is. These storage systems are introduced as a potential solution to support peak load levels while reducing planning costs and environmental damage. The authors naturally apply mandatory constraints to the network and test out their method in a grid that is due an expansion to evaluate the impact of their methodology. There is also a consideration for different types of ESSs with various capacities in order to deeply study the best way to introduce them into the grid. According to the authors, the study's primary goal was successfully accomplished as ESS implementation increases planning flexibility and significantly reduces GEP (Generation Expansion Planning) and pollution. As seen in Fig. 3, Hemmati et al. analyze the difference in planning cost for scenarios, with and without ESS, with most situations being favorable to the usage of ESS. The different “Stages” represent different combinations of generation mix and type of ESS. Once again, the blinding conclusion is that ESS must be considered in every expansion/reconfiguration planning since it benefits the network in many ways. The only situation where Hemmati et al. found storage systems to be inefficient was in stage 3, and this was due to the majority of generation in this scenario coming from oil-based generation as well as the fact that in that scenario, a smaller-scaled ESS was input, “forcing” the network to overproduce to compensate for the lack of storage, once again supporting the fact that ESS is essential especially with the impending uprising in RES, which, as mentioned before, desperately call for flexibility measures.

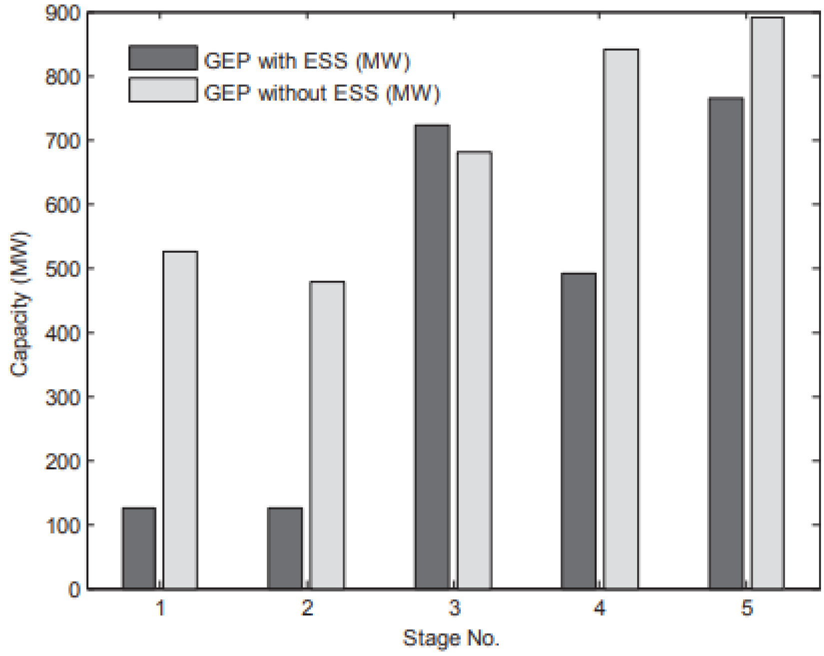

Figure 3 - Impact of ESS on costs associated with a network (Source:[18])

Xue et al. in [19] analyze the optimization of DNs with maximum DG consumption, considering different types of generation such as wind, photovoltaic, and more, while also considering the factors of energy storage devices and flexibility in the network. The optimization model aims to provide an efficient method of optimization planning method for maximization of distribution generation. Conclusions show that the presented method satisfies restraints while benefiting the DN economically.

Antweiler in [20] applies models of electricity storage, which need to be taken into consideration and are much more prominent and on the come-up in recent times. He seems to believe that applying ESSs to grids is the answer to a more feasible price forecasting strategy. With the aid of economical theory, Antweiler also quantifies how profitable ESS can be by aiming to nullify, or at least minimize, the number of episodes where prices become negative. The author believes that, going forward, the coupling of ESS and intermittent renewable energies is the way to go since it brings out the best in both worlds. Antweiler draws four major conclusions, the first being that the impact of ESS is directly correlated to how accurate forecasting is, meaning that if forecasting hindsight is perfect, the value of storage in grids skyrockets. Secondly, it is understood that there needs to be a balance between size of storage systems and chosen batteries since the usual correlation is that a larger ESS means using cheaper batteries, leading the author to believe that finding a way to reduce battery costs needs to be a priority in order to allow for more freedom in grid planning, minimizing dampening effects. Another conclusion was that supply-sided storage was not economically viable, which ties into Antweiler's last conclusion that consumer-sided storage seems to be the way to go, supported by the fact it drastically cuts losses and transmission costs and improves flexibility.

In [21], Wu et al. match different types of renewable generation with different types of energy storage to find which are more interesting for application. The authors consider three types of storage systems in thirteen different application scenarios, varying in generation, transmission, and demand values. These scenarios are then matched with six types of RES and analyzed according to their number-based Multi-Criteria Decision-Making Analysis (MCDA) method named PROMETHEE-II using an eight-step fuzzy framework. Fig. 4 shows how economically interesting each combination for a different scenario is, with results showing that photovoltaic seems to be the most prevalent common denominator in aspiring situations. As for the generation side of the analysis, the combinations of "PV and Compressed Air Energy Storage (CAES)", "Hydro and CAES", "Wind and CAES" and "PV and CAES, Hydrogen-Fuel Cell (HFC)" seem to be the most optimal solutions for policy and decision makers for the future in order to apply a large-scale modulation of current grids for a bigger penetration of RES. In the transmission part of the analysis, "PV and Ni-Cd batteries" seem to be the favorable decision. The author concludes that "PV and CAES/Ni-Cd batteries" provide the best outcome for terminal applications. The biggest draw from this analysis is that PV generation seems to be the common denominator in all preferable cases, shortly followed by wind power, supporting the idea that future grids should aim for a healthy balance between wind and PV generation.

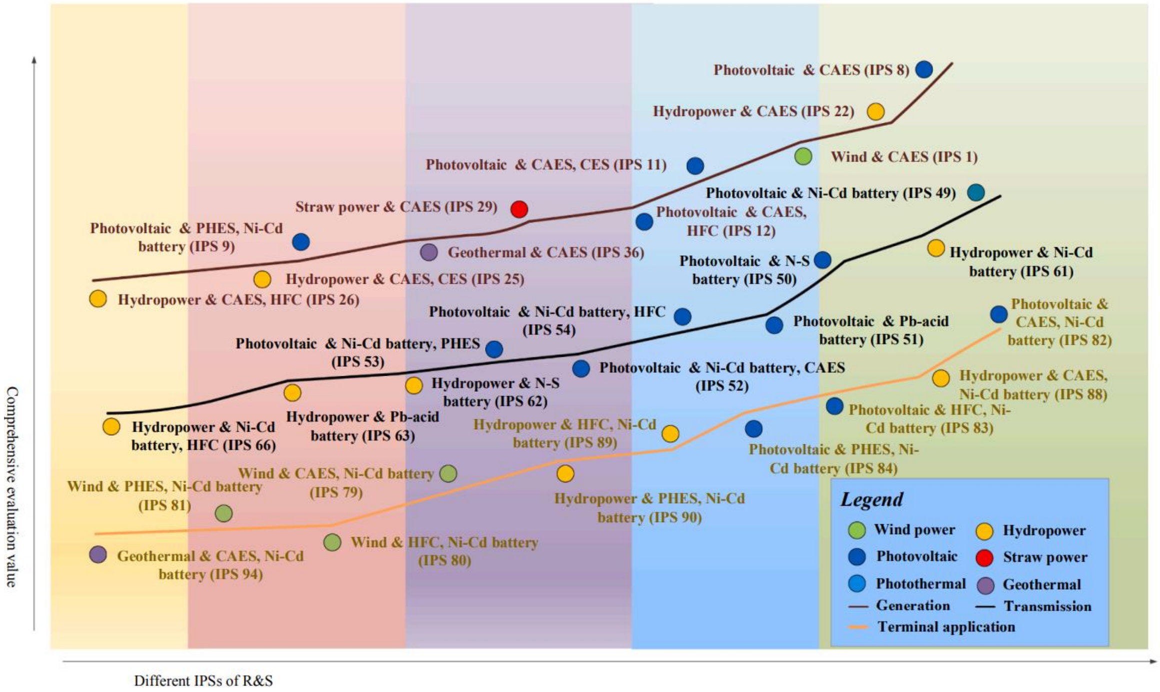

Figure 4 - Economic interest of each combination of generation and ESS (Source:[21])

Garmabdari et al. [22] study different grid configurations in order to find the most suitable one. Cogeneration offers excellent efficiency, which the authors believe is the key to significant economic profitability in grids. While the author's main focus is to prove that cogeneration is superior to separate electricity and heat generation, the main conclusion also proves that adding energy storage is noticeably helpful in managing a grid. The author proves that the proposed measures are especially helpful in peak demand hours (18h-21h).

2.3. Optimal Network Planning Considering Uncertainty

The optimal planning of distribution grids can be very challenging to get right because of the number of factors it entails. With the emergence of new technologies and a shift to renewable generation, uncertainty becomes a major factor in decisions since it implies that most data and inputs cannot be streamlined. Many types of uncertainty play a major role in most optimization models for grid planning, from input analysis data of wind to seasonal impacts to forecasting demand and supply. Fig. 5 shows the types of uncertainty that are presumed to see an evolution in the future and can be associated with a formulated model. As a result of how much uncertainty surrounds energy systems, it must be considered to ensure the reliable operation of systems and their proper stability [23]. It is also worth noting that, while the current energy supply already carries uncertainty, it will grow substantially in the future, as deviations from actions such as an increase in RES which reduce system flexibility and forecasting accuracy drastically [23], [24].

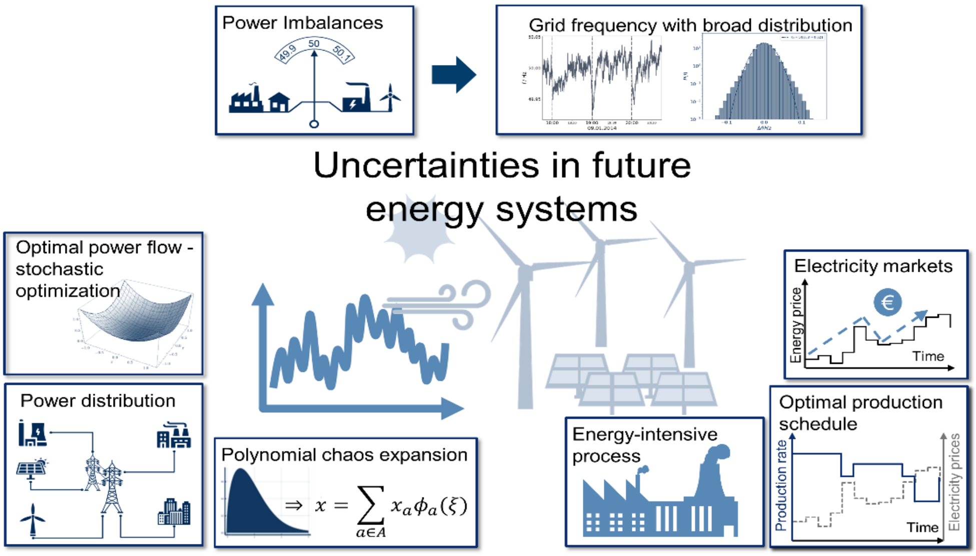

Figure 5 - Types of uncertainty predicted to see an uprising in the future (Source:[24])

Table 4 aims to group some literature that addresses uncertainty in their models, varying from solar and wind power, load and demand, battery-related data, seasonal data, and even urban uncertainty.

Table 4 - Optimal network planning considering uncertainty literature

Ref.	**Focus**	**Main Objectives**	**Used Techniques**	**Limitations**
[25]	Transmission System Expanding	Choose the best way to expand a transmission system	Branch and bound that uses a network flow approach	Small sample grid
[26]	Long term distribution network planning considering urbanity uncertainty	Mitigating effects of urbanity uncertainty while planning distribution network	Genetic algorithm, and branch exchange method	Author concludes there is economic benefit but does not consider implementation cost

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[27]	Optimal sizing of PV DG with uncertainty	Minimizing average system active power losses, while considering power quality constraints	Monte Carlo for solar radiation, temperature, demands, and substation voltages	While the model allows for adaptation, line current limits are not considered
[28]	DG planning and reliability assessment	Determining the minimum number of states to represent the behavior of wind and PV generation	Self-developed algorithm	Work does not propose potential reconfiguration or addition of lines
[29]	Bi-level approach to DN and RES expansion planning with DR	Minimize generation and network investment cost while balancing demand Minimize consumer costs	Two-level problem KKT complementary constraints (adapted from [30]) to recast model to MILP solved by branch-and-cut	Authors do not consider potential storage systems to facilitate response
[31]	Management of uncertainty related to RES on DG	Finding a new way to manage uncertainty in RES	Probabilistic-based approach as opposed to traditional level-based methods	Not acknowledging potential reconfigurations to best mitigate the issues
[32]	Incorporation of uncertainty and reliability in DN planning with DG	Identify the best location, type, and installation time of several assets under demand and RES uncertainty and minimize investment and operational costs	Iterative algorithm with a stochastic programming-based model Equivalent MILP formulated deterministic-based model for comparison	The authors indicate that, although the model allows for adaptations to input ESS and DR it was not done on this literature
[33]	Plan of DN that operate mainly on solar and PV power	Maximizing social welfare considering uncertainty of wind/PV	Deterministic model Multi-configuration multi-period market-	Since the focus is RES, ESS should be considered

Ref.	Focus	Main Objectives	Used Techniques	Limitations
			based optimal power flow	
[34]	Planning of renewable DG and CO_2 emissions	Minimizing the net present value of investment and operation costs as well as CO_2 emissions	Stochastic model implemented in AMLP language solved with CPLEX	Author points not including mathematical models' uncertainty as a flaw
[35]	Expansion planning considering investment and CO_2 emissions	Minimizing the net present value of investment and operation costs as well as CO_2 emissions	Two-Stage stochastic model solved with the ε-constraint method	Authors indicate they could potentially add more objective functions for precision of results

A wide variety of uncertainties can be inserted into a model, from outage rates to urban uncertainty to wind and solar outputs. The following literature inputs FOR (Forced Outage Rates) uncertainty into their model as Choi et al. in [25] analyze system expansion methods while considering future uncertainties. The exposed procedure optimally allocates transmission lines and their capacity while considering uncertainties associated with the matter, such as the FOR of grid components such as transformers and lines. The problem is resolved through a probabilistic branch and bound algorithm, and the results show that the proposed methodology presents better results than the other benchmark methods.

As mentioned, some literature considers urban uncertainty, such as the following piece of literature [26], which aims to provide a new DN planning algorithm that focuses on urban uncertainties, and this is done by means of selection of embranchment points that serve as a "meeting point" to transmission lines, to then redistribute to the consumer. These embranchment points were meticulously chosen to be high accessibility points that facilitate the connection between interest spots by combining neighbor loads. The optimal configuration of the embranchment points was found via genetic algorithms. Then, the collected data was input into a branch exchange method to optimize transport routes with predetermined branching points. Salehi et al. conclude that this approach to planning in urban areas brings several advantages, such as simplicity of operation and costs and decreased outages. It also finds that should outages occur, they are cheaper and easier to fix, given the smaller number of lines and connections.

The most common type of uncertainty is associated with solar and wind levels and load. Some authors also include uncertainty related to energy prices, for example. Reference [27] aims to find the optimal size of PV DG in systems while considering uncertainties such as radiation and temperature. A probabilistic approach is used to design the optimal size of PV DG in a system considering both generation and load stochastic variables. The authors study their proposed methodology on a 51-bus network, and it is based on actual hourly solar radiation, ambient temperature, and typical harmonical currents. The authors' main conclusion is that the background harmonic level is the most important factor that needs consideration when planning the size of PV generation.

Identifying the level of uncertainty that will be utilized in the work is crucial to preparing optimally. The work [28] finds the ideal level of states that should be considered to describe solar and wind power behaviors. The author analyzes several states and compares the outcome data on different levels, such as power losses (see Fig. 6). Research such as this one is crucial since it allows authors to know how many scenarios to use and research optimally by saving computational time and resources. Alotaibi et al. researched the subject in three different time samples: yearly, seasonally, and monthly. The conclusion is that, as expected, monthly modeling is the most accurate representation of wind speed and solar irradiance in hindsight. Still, seasonal modeling is also found to be adequate when analyzing annual patterns since it provides results close to the monthly model and accurately maintains the correlation between renewable resources output and demand. Final results also show that there is a significant drop in losses and costs for networks with dispatchable storage, supporting the fact that it is crucial to consider them in potential reconfigurations or expansions of networks.

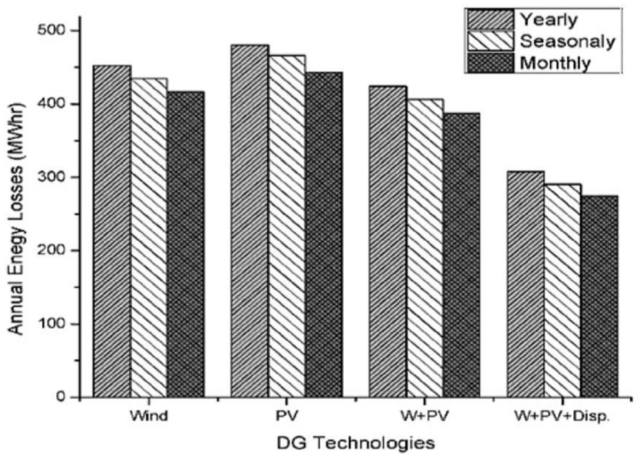

Figure 6 - Results of different DG technologies on energy losses (Source:[28])

Asensio et al. in [29] present a bi-level model for DN and RES expansion planning under the assumption that a DR framework is implemented, which is crucial in modern line planning. The authors propose an upper-level problem tying into integrating DR to prices over time, which is connected to a lower-level problem that aims to minimize overall consumer payment. The transition process to Karush-Kuhn-Tucker (KKT) follows [30]. The authors conclude that, for medium and long-term planning, DR reduced costs while accommodating a smooth expansion to an increased percentage of renewable generation.

In [31], Montoya-Bueno et al. stress the importance of DG, so they developed this work to provide alternatives to managing uncertainty to allow for a more precise forecast with mitigated error. To do so, the authors use a probability-based method, which they compare to traditional level-based methods, and they find out that the performance is superior. The main draw from the analysis is that a significant reduction in costs is obtained because of a smaller gap between forecasted supply and demand, meaning that there are fewer occurrences of needing to compensate for high demand because of low generation and, more prominently, the contrary, because of how unpredictable RES are, there seemed to be lots of periods where generation was being forecasted for a higher value than needed in hindsight, and the number of these situations was also reduced.

Munoz-Delgado et al. in [32] provide options for the location of the ideal placement of feeders, transformers, and DG while incorporating uncertainty and dependability in networks with DG. As well as optimal location, the proposed model also chooses the best type and time of installation. To grasp the sample size that should be studied, the authors devised an iterative algorithm and selected the best financial outcomes. Each outcome was then studied with the authors' proposed method and similar benchmark methods to prove the superiority of the authors' proposal. The conclusion was that there is a clear need for precision in the effect of reliability on decision-making, which could very well lead to different expansion plans from the traditional approaches.

In [33], Mokryani et al. aim to plan DNs with a high percentage of wind and PV generation, with different configurations of scenarios. These scenarios affect the following variables: wind speed, solar irradiance, load demand, and operational status of WT and PV cells. All the different configurations are compared to assess which is the better option. The authors conclude that different scenarios bring diverse advantages with different characteristics, such as the time of day it is most profitable. Therefore, Mokryani et al. believe that a combination of scenarios is the ideal procedure to take the most economic benefit. All the configurations are seen in Table 5 (lower side). They are then analyzed (Fig. 7) to find that only having WT and PVs on two of the four selected buses is the best approach in terms of produced power and price, with configuration 10 being the exception, which is due to voltage and thermal constraints according to the authors. While configurations 11-15 seem good regarding price and power, they drastically affect the social welfare scale since four locations are affected and, therefore, are not optimal. These findings support the idea that meticulous planning is crucial since an over-expansion could be as damaging as an under-expansion. The analysis was also done in two scenarios (see Table 5, upper side).

Table 5 – Scenarios (upper table) and configurations set for the study (lower table) (Source:[33])

Scenarios	CVC	PFC	PF = 0.95 lagging
A	-	-	✓
B	✓	✓	-

Multi-Configuration	WT and PV status/location			
	Bus 2	Bus 24	Bus 6	Bus 14
1	1	0	0	0
2	0	1	0	0
3	0	0	1	0
4	0	0	0	1
5	1	1	0	0
6	1	0	1	0
7	1	0	0	1
8	0	1	1	0
9	0	1	0	1
10	0	0	1	1
11	0	1	1	1
12	1	0	1	1
13	1	1	0	1
14	1	1	1	0
15	1	1	1	1

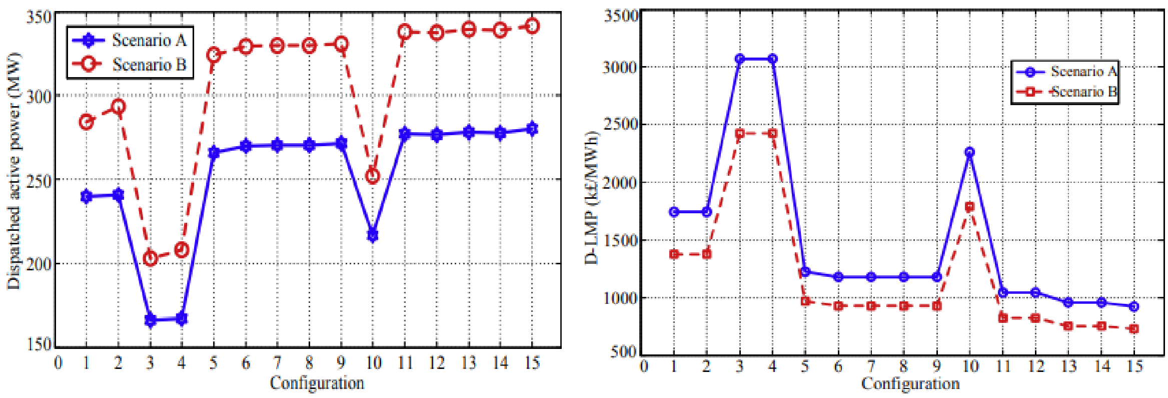

Figure 7 - Analysis of different combinations of scenarios by dispatch usable power (Source:[33])

Reference [34] proposes a stochastic programming model for planning networks with renewable DG present while considering CO_2 emissions. This model is a two-stage model for expansion planning of Electrical Distribution Systems (EDSs), considering uncertainties derived from the DG units, demand, and price. The main objective is minimizing costs, but Lima et al. also optimally plan the minimal amount of CO_2 emissions on a 24-bus grid. A comparison between the proposed model and a deterministic counterpart was made. The authors found the deterministic approach to present lower total costs. However, this model is not prepared to deal with future uncertainties such as demand growth or price fluctuations and is unviable.

Similar to work done in [34], Lima et al. in [35] propose a two-stage stochastic model for expansion planning where CO_2 emissions are considered. Again, the two objectives are minimizing both investments and CO_2 emissions. Scenarios to model the problem are done using a Mixed-Integer Linear Programming (MILP) formulation with correlated uncertainties to wind, irradiation, and demand. The model allows for investments on reconfigurations such as substations, circuits, and DG, and the model is tested on a 54-bus grid. The authors find that, as expected and shown in Table 6, a lower CO_2 emission is correlated to a higher investment cost. The solutions are different variations of DG placement, etc., with solutions 1 and 572 being the most extreme scenarios of maxing out generation units. Solution 438 would be the most suitable since it finds the best balance between saving money and minimizing CO_2 emissions.

Table 6 - Correlation between investment, CO_2 emissions and an indicator of quality (Source:[35]

Results for selected solutions in Case III.

Solution	CO_2 Emissions (%)	OF_1 (kUS$)	OF_2 (tons)	μ_p
1	100.00	178099.28	305311.47	0.5000
10	99.68	178287.03	304346.33	0.5034
50	98.32	179108.33	300188.72	0.5176
100	96.65	180096.38	295078.43	0.5357
200	93.40	182161.35	285161.47	0.5668
350	88.54	185605.52	270311.47	0.6038
438	85.67	188290.38	261561.47	0.6079
572	81.32	196546.17	248290.56	0.5000

2.4. Optimal Network Planning Considering Both Energy Storage Systems And Uncertainties

Much recent literature has gravitated towards introducing uncertainty as well as ESS into their modeling options, and it makes perfect sense considering the impacts recent trends have shown to have on electricity networks. With the growing amount of RES penetration, there needs to be a consideration for uncertainty related to these new generation sources, as well as uncertainty related to other factors such as load, demand, battery characteristics, and seasonal variability, among other things. Many specialized literature have shown that one of the best ways to mitigate the issues that RES increase brings, such as lower flexibility, is storage systems. So naturally, the coupling of ESS and uncertainty is key to a well-structured model, be it of reconfiguration, expansion, or initial networks planning [36], [37]. Table 7 aims to address literature that considers the topics.

Table 7 - Optimal network planning considering ESSs and uncertainty literature

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[38], [39]	Planning of DN with RES expansion considering DR and ESS	Plan network expansion considering DG, DR, and ESS to maximize social network benefit	Stochastic-programming-based model vs equivalent MILP deterministic	Authors indicate poor forecasting accuracy as a possible limitation

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[40]	Large-scale energy resource management in SG	Minimizing operation cost while addressing issues such as variability of demand, RES, EV's…	Two-stage stochastic model and Benders' decomposition for model simplification	Not tackling nonlinearities, even if planned for future work.
[41]	ESS planning with Markov model considering battery uncertainties	Optimal ESS size and location, while minimizing several related costs	Markov-model to reduce restraints, stochastic models for power and loads	Not determining candidate buses for installing and exploring the ESS as an ancillary service
[42]	DG and ESS planning	Finding optimal location of ESS and DG while minimizing costs	Two-stage model formulation MINLP Enhanced PSO	Authors indicate that improvements in comprehensive stability and reliability could be done
[43]	Hybrid ESS planning on community systems	Determining optimal size and location of HESS	Two-stage stochastic programming and Deterministic model for comparison	Ignoring degradation costs of ESS
[44]	ESS planning in a PV-heavy network	Determining the optimal ESS planning strategy	Data-driven deterministic model for uncertainty modeling and two-stage stochastic model	Authors believe that not considering uncertainty related to other grid points is a flaw
[45]	Expansion planning with DER	Minimizing environmental and financial aspects of planning an expansion	MILP model on AMPL language solved with CPLEX	Not exploring robust optimization which the authors perceive to be a weak point in specialized literature
[1]	Expansion planning considering storage	Minimizing losses, PGC, LC and investment costs Finding optimal	Two-stage stochastic model	Not including multi-period phase investment and

Ref.	Focus	Main Objectives	Used Techniques	Limitations
	and seasonal uncertainty	type/location of new lines and ESS Improving network reliability through not supplied minimization	Deterministic model for comparison reasons	uncertainty related to projected scenarios

References [38] and [39] complement each other as a two-part work, where in the first paper, Asensio et al. describe the model used to integrate DR and ESS in the proposed network. The authors believe previous literature did not consider ESS and DR to be on the same standard of importance as the grid's remaining “to be determined” factors. In this way, they believe their proposed model of equal footing for all these factors is appropriate. The problem is formulated via a stochastic model aiming to maximize net social benefit, with an equivalent deterministic counterpart (MILP) for means of comparison. With this first part of the paper, the authors outline the location and size of DG and ESS, with the potential for adding, eliminating, or replacing assets.

In the continuation paper ([39]), the authors apply their model to a case study modeling for the load, wind, and solar generation uncertainty. The authors proclaim that ESS and DG are required in future expansion planning since they prevent overinvestments in costs associated with remodeling the network, supporting the conclusions previously analyzed in [33].

In [40], Soares et al. aim to solve the increasing issue of scheduling and committing units on a large-scale smart grid. The authors address uncertainty meticulously since they find it crucial to mitigate potential unforeseeable issues. The focus is to figure out countermeasures for alarming issues such as variability of demand, RES, an increase in Electric Vehicle (EV) penetration, and market price variations, all to minimize the entire operational costs. The proposed model, which uses Benders’ Decomposition, is implemented on a 180-bus grid on Leiria with a high percentage of penetration of RES. The slave portion of the decomposition aims to apply the network constraints, and the current model allows for the insertion of new possible uncertainties that may come up in the future. The overall conclusion follows the common trend in which DR and ESS are shown to stabilize the issues. The authors’ final dispatch volume conclusion is in Fig. 8, where the calculated uncertainty is also considered. The two test cases (A and B) are two of the scenarios considered by the authors, with these two cases being the most extreme situations, A being a scenario where ESS and DR are considered and B where DR and ESS are not considered.

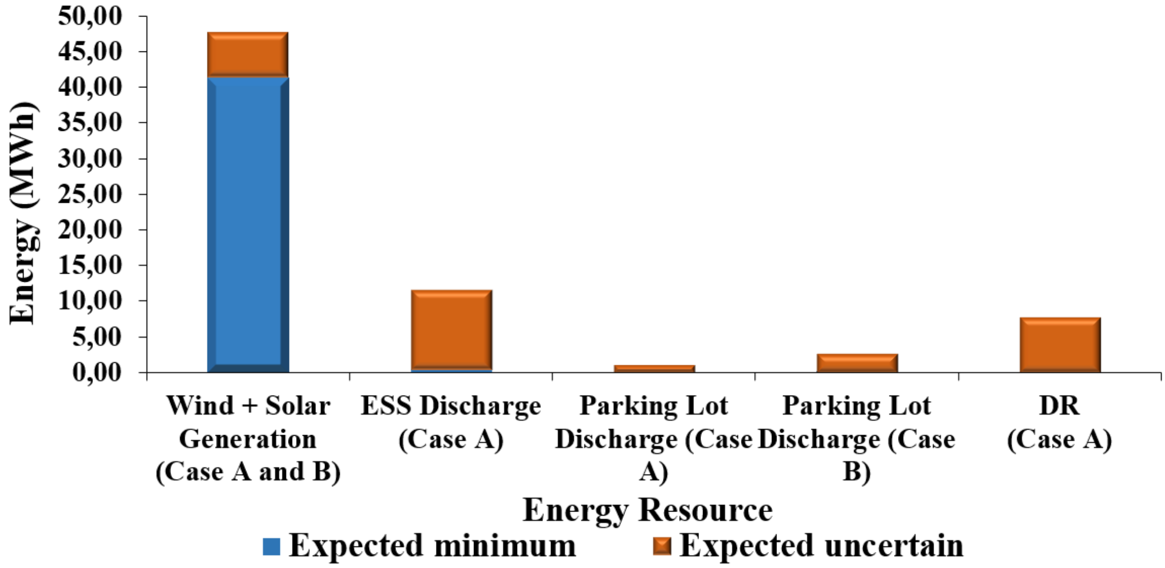

Figure 8 - Final dispatch volume analysis with a margin for uncertainty in different cases (Source:[40])

In reference [41] ESS planning and uncertainty related to the chosen systems, such as battery characteristics, load, and wind power, are introduced. The paper aims to determine the optimal size and capacity of the storage systems while minimizing investment, replacement, and Operation and Maintenance (O&M) costs and energy losses, maximizing Annual Arbitrage Benefit (AAB). The authors deem the problem too large-scale to be tackled through traditional optimization models. Therefore, they assume the powers and loads to be stochastic problems and implement Markov models to reduce the number of variables and constraints. The states of the Markov model are obtained through a clustering fuzzy-c-means algorithm. The authors conclude that tariffs associated with storage affect the results significantly.

Qiu et al. in [42] also aim to plan the optimal location and size of ESS, but also DG, with a special focus on the integration of wind, trying to minimize the sum of costs with the help of a two-stage model. The model is applied to a 15-bus grid, and the authors conclude that the proposed approach method was supported by the results, showing that risk-seeking is preferable if wind penetration increases, meaning policymakers should invest in the matter.

In [43], a two-stage stochastic programming model is used to plan Hybrid Energy Storage Systems (HESS), where there are battery and thermal storage tanks. Similar to the base of this thesis ([1]), the authors consider a variety of uncertainties. Then, a study is done to understand seasonal variations' effects on the proposed method. Still, there is not a defined uncertainty related to this seasonal variability, which is one of the main focuses of the model of this thesis. Shen et al. need to consider seasonal scenarios since one of their targets is minimizing costs on HESS. Therefore, they address temperature-related issues such as thermal inertia on the heating network, space heating demand, and domestic hot water. The first step of this paper is solved through a two-stage stochastic model to coordinate long-term HESS allocation and short-term operation. For comparison reasons, a deterministic model is also developed. The authors showcase that HESS enhances operational flexibility with minor investment costs.

Lu et al. in [44] establish uncertainty models through a data-driven method and Distributionally Robust Optimization (DRO) to determine optimal ESS characteristics. The authors utilize Wasserstein-metric-based ambiguity for the probability distribution of random variables. This problem is expanded into a two-stage DRO problem, which minimizes expected operation cost on the worst possible scenario case, and this is then formulated into the Mixed-Integer Second-Order Cone Programming (MISOCP) problem, solved by optimization solvers. This is tested on a 123-bus grid, and real solar and load variance data is used, which is essential for DRO methods since they do not rely on theoretical data and use historical data instead. The authors found the DRO method to be the more satisfying approach if considering monetary minimization. The authors also decided to study the number of optimal situational scenarios to consider (different PV, ESS, capacitor, etc. values), evaluating it by studying computational times and outcome results. As seen in Figs. 9 and 10 naturally, with a higher sample size comes an increase in computational time, and the authors figure that at a certain point in sample size, the results stabilize, meaning this needs to be considered since it is a waste of computational resources.

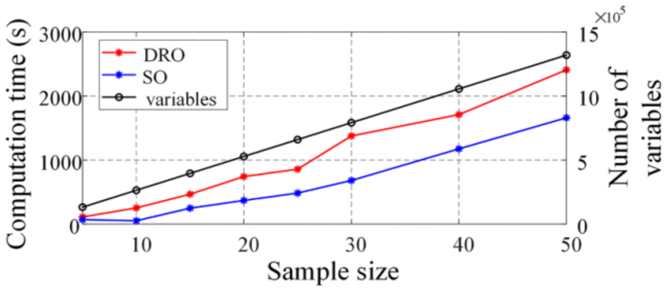

Figure 9 – Sample size related to computational time (Source:[44])

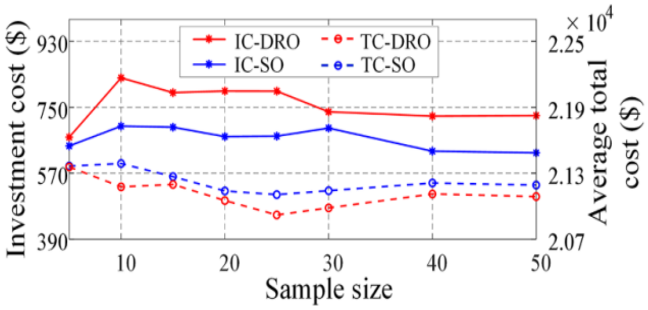

Figure 10 - Sample size related to total cost (Source:[44])

In reference [45], Lima et al. follow a similar proposed model to that of [34] and [35] along with other common uncertainties, energy storage is also considered to mitigate the effects of these same uncertainties. A MILP model is used to consider DG, ESS, and EV charging stations in order to reduce total related costs as well as CO2 emissions while taking into account EVs. All linked uncertainties are also considered. The method was applied to a 24-bus grid and solved using CPLEX. The authors believe this work is a leap in quality over previously mentioned literature due to simultaneous investments in substations, circuits, EVs, DG units, and ESSs, resulting in a lower cost than ever before. All this integration aims to reduce the need for relying on substations, which would substantially decrease costs and CO_2 emissions.

Lastly, reference [1], the base model supporting this thesis, provides an expansion plan that considers possible investments in storage and considers the seasonal effect on demand and RES. The proposed model uses a stochastic methodology to be applied on large networks with high percentages of RES in a Smart Grid (SG) context. The proposed model also allows for new power line locations and types, sizing, and allocating ESSs. The model was applied to a 180-bus grid in Leiria, Portugal. Then, a comparison between the proposed two-stage stochastic model and a deterministic counterpart is made, which shows how favorable the stochastic one is by avoiding higher investment costs, as seen in Fig. 11. A lot of previously analyzed literature in this document compares stochastic to deterministic models, and Canizes et al. show here exactly how favorable the stochastic model is in each characteristic. The current season probability tree diagram, which is planned to be further segmented in later stages of this thesis, is as follows in Fig. 12, and it shows that, for the purposes of scenario building, there is a consideration for seasonal changes. Future planned work was associating a plethora of uncertainty-filled scenarios to implement in each of these time periods. Collecting solar, wind, demand, and generation data was planned for each scenario, which would be studied independently.

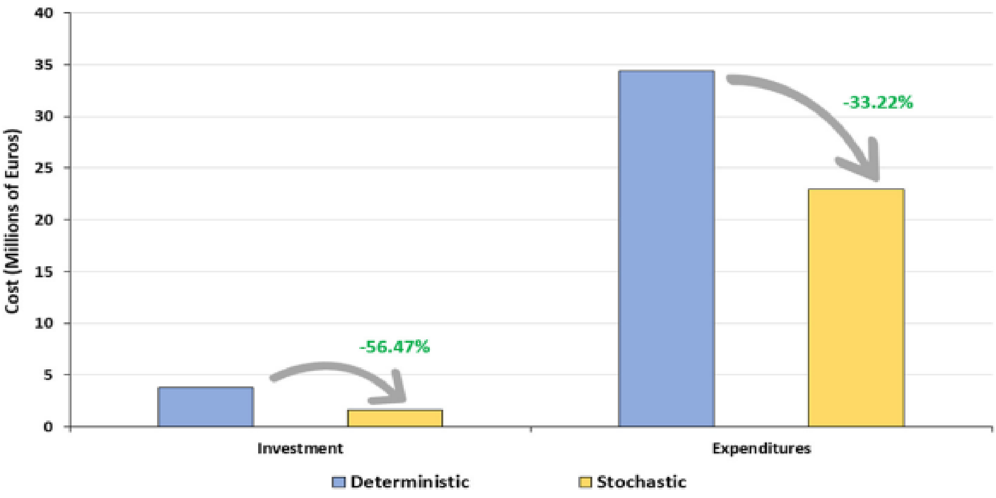

Figure 11 - Comparison between deterministic and stochastic models (Source:[1])

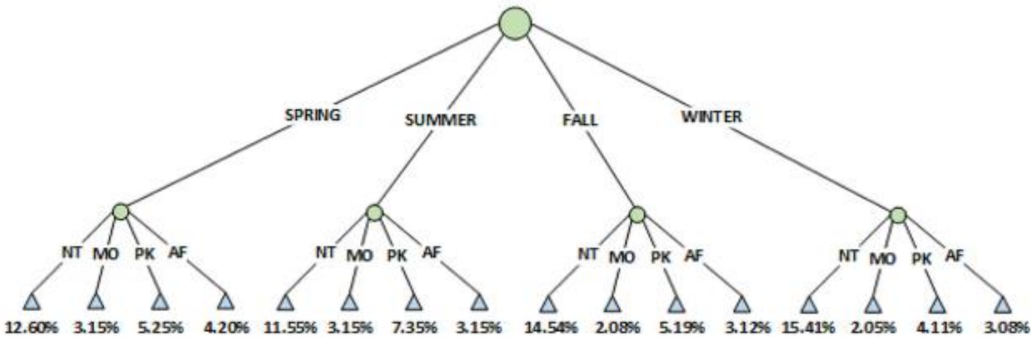

Figure 12 - Current seasonal probability diagram (Source:[1])

2.5. Remuneration of Distributed Resources

The topic of remuneration of DG is a necessary discussion in modern networks, especially with the network getting more and more complex and unpredictable with an increase in RES penetration. There is a need for solid consideration for these contributors who are part of a more extensive network. However, the topic is not extensively studied in recent literature, at least not as much as it should be. Table 8 addresses some current works that addressed the remuneration of resources.

Table 8 - Remuneration of distributed resources literature

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[46]	Improve Regulatory Approach for Remuneration	Combining several state-of-the-art regulatory tools to get around information asymmetries	Ex-Ante and Ex-Post Regulatory processes and combination of both	Only considering allowed TOTEX revenues, and permanent need of manual alteration
[47]	Pricing of DG by node	Study each node individually and remunerate accordingly	Correlating the annual cost with the power flow to find used and unused capacity	Pre-chosen location for every element, not optimal allocation
[48]	DLMP to aid congestion management and voltage support	Minimizing total operational costs while remunerating DG units	Derivations of Lagrangian function and sensitivity factors and MISOCP	Authors consider reconfiguration of the feeders but not the associated cost
[49], [50]	Managing congestion and adjusting DR	Study remuneration according to needed DR	LMP on a real Danish network	Inaccurate estimation of spot market price and coordination of day-ahead market and real-time market
[51], [52]	Resource managing techniques using aggregators	Minimizing associated costs while remunerating DG through different methods	Mathematical model to manage resources	Authors plan to adapt future work to allow for the increase in demand
[53], [54]	Adding a classification phase to remuneration and evaluating it	Fairly remunerating of participants of the market in addition to minimizing operating costs	Mathematical model to manage resources	Not considering ESSs even if it is planned for future work
[55], [56]	Planning for the increase in EV number	Maximizing the aggregator’s profitability, while minimizing consumer costs	Real time-varying prices and on a mathematical model	Authors indicate thin line between balancing consumer costs and aggregator profits

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[57]	Impact of wrong foresight on DG dispatch and remuneration	Maximizing social welfare, while studying varying degrees of foresight inaccuracy	Stochastic model for foresight with risk measurement (CVaR)	Not providing adaptation for ancillary services

Regarding remuneration, in [46] the authors offer a new approach that combines several methods and tools to manage uncertainty and overcome the obstacles of unclear data. The goal is to reduce the total involved cost and the number of associated forecasting errors.

Many authors aim to calculate the associated remuneration through Locational Marginal Pricing (LMP), such as [47] in which the authors propose a method to reimburse DG with LMP in distribution systems with radial configurations. Similarly to the analysis in this thesis, the authors consider both used and unused resources. Bai et al. in [48] aims to give attention to managing congestion and prices (through Distribution Local Marginal Pricing (DLMP)) while taking into consideration both active and reactive power, also addressing the voltage support through MISOCP.

In [49], the congestion is computed ahead of time, and DR is calculated to respond as needed. This information is then utilized to determine the relevant remuneration value, which also considers the interactions between the unit to be remunerated and the Distribution System Operator (DSO). Reference [50] adopts a similar strategy, although one is implemented on a network managed mainly by non-RES.

The authors Faria et al. in [51] present a technique to manage resources using an aggregator to provide various combinations of aggregation and payment schemes. These authors investigate multiple strategies, including hierarchical and fuzzy c-means clustering, in their work in [52]. These strategies are utilized to aggregate and monetize energy resources.

Even though the primary focus of the study is on compensating contributors and reducing operational costs, Silva et al. in [53] offer a new stage to the already existing scheduling, aggregation, and remuneration, which is the classification stage. This stage aims to assist the aggregator in operating situations. Similarly, in [54], these authors contribute by striving to grasp exactly how aggregating affects the final values of pay for each contributor. In other words, they are trying to determine how the aggregation affects the final pay values. The authors study four methods, the four most common in literature works, described in Table 9, with the results showcased in Table 10. The current thesis approach is method 1.

Table 9 – Definition of the methods (Source: [53])

Method	Type of remuneration	Description
1	Individual	Each consumer receives according to the contracted tariff (fix tariff)
2	Average	Each consumer receives according to the average of the tariffs of the group that belong (fix tariff)
3	Maximum	Each consumer receives according to the maximum of the tariffs of the group that belongs (fix tariff)
4	Maximum with Index Tariff	Each consumer receives according to the average of the tariffs of the group that belongs. The tariff is formed through the sums of fix tariff and index tariff

Table 10 - Remuneration of the methods (Source:[53])

Method	Whole Week [m.u]	Weekend [m.u]	Week Days [m.u]
1	885,456.59	195,349.72	690,146.86
2	880,536.12	288,875.35	646,503.79
3	1,278,258.91	309,979.03	802,682.48
4	794,850.47	190,483.39	521,568.37

Although the remuneration aspect of network planning is vital, as discussed, it's the combination of several considerations that offers the best possible representation of reality. Adding uncertainty to a model is necessary for modern planning, and ESS are also very needed [58].

In [55], Sarker et al. plan ahead for the possible increase in the number of circulating EVs. The main objective is maximizing the aggregator's profitability while minimizing the consumer's costs by responding to time-varying prices and adding potential incentives to those who contribute the most to maintaining the network within its limits. The authors prove that, as such, an increase in EV penetration in modern networks is possible. Similarly, in [56] Ma et al. use real-time adjustments to calculate the proper incentives to award to the demand side of the network. In their proposed model, an enhanced Arrow'd Aspremont-Gerard-Varet (AGV) mechanism is used, and the consumers are penalized/rewarded according to their consumption record. According to the authors, this is exceptionally effective in making consumers self-aware of their usage of electricity and benefits both users and suppliers.

Lastly, Kim et al. in [57] study the impact of errors in forecasting on optimal deployment and the remuneration of the respective resources. Here, the authors develop two methods in hindsight, one perfect and one imperfect, and as such, assess the respective impacts in the results. These models can accommodate net metering, value stack, and DLMP-based remuneration. Kim et al. find that inaccurate foresight leads to a monetary loss of at least 1.6% across all scenarios.

2.6. Risk Assessment on Network Planning

Risk assessment is necessary to plan the DNs adequately and precisely, since planners must consider, even if improbable, possible unfavorable circumstances (extreme events). Implementing risk aversion through, i.e., VaR and CVaR, might make the overall planning cost slightly higher. Still, in the case of an extreme event occurring, which would otherwise cause major costs in the network, the network is more prepared to adapt to those situations to mitigate the consequences. While some current literature addresses risk aversion, few consider all relevant topics simultaneously (RES, ESS, uncertainty, remuneration of resources, etc.). Table 11 shows some relevant literature on this topic.

Table 11 - Risk assessment on network planning literature

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[59]	CVaR based planning model with ESS and RES	Minimizing the total costs associated with the network	Two-stage mathematical model and Backward scenario reduction method for computational issue	Computational burden of the problem and not considering DG remuneration
[60]	Expansion planning with uncertainty and CVaR	Minimizing the expected total cost, through CVaR	Mathematical model solved through mean-risk stochastic models	No consideration for remuneration of resources
[61]	Optimal operation of electric-heat-hydrogen IES through CVaR	Minimizing day-ahead, real-time and risk costs	Mathematical model solved through GUROBI in Python	Input characteristics not fully realistic according to the authors
[62]	IES model with ESS and CVaR	Minimize total involved cost, including CVaR	Mathematical model formulation, using YALMIP in MATLAB and GUROBI	No remuneration of resources and high computational burden

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[63]	Voltage control and thermal flow	Coordinate the dispatch of active/reactive power as well as thermal flow	MILP model with CVaR solved with CPLEX on GAMS	The authors point no real-time adjustments and not using state-of-the art forecasting as flaws
[64]	Comparison of several algorithms for solving ERM with CVaR	Reducing total costs while managing dispatch problem	Several different algorithms	High model complexity
[65]	Optimal ESS control minimizing CVaR	Minimizing total costs as well as CVaR	Multivariate Gaussian distribution and two-stage stochastic model	No resource remuneration apart from the ESS
[66]	Extreme event risk assessment based on CVaR	CVaR minimization	Mathematical model for extreme events	Not considering any other network aspects apart from risk
[67]	Robust ERM incorporating CVaR	Minimizing total costs and CVaR	A self-made metaheuristic	Not implementing intraday management according to the authors
[68]	Transmission network expansion planning	Minimizing total costs and CVaR	MILP model solved with CPLEX	Authors point computational burden, no multi-period and reliability and flaws
[69]	Planning of the DN structure	Minimizing the total distribution system planning costs	Mathematical model solved with a branch exchange algorithm	Using a low amount of scenarios due to computational burden
[70]	Machine learning for stochastic optimal planning	Minimizing total power losses	Markov chains and copula functions for weather forecasting for stochastic models	Not considering a lot of network planning essentials such as ESS and uncertainty

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[71]	Optimal configuration planning of multi-energy systems	Minimizing the total multi-energy systems cost	Two-stage MILP model	Not considering the costs of generation
[72]	Network planning considering EV charging stations and carbon taxes	Minimize the net present cost for investment, operation, and risk	Mathematical model for multi-period planning of EDSs and DERs	Not applying incentive policies is pointed out by the authors, as well as risk related to CO_2

Regarding the formulation of the risk assessment through VaR and CVaR, most specialized literature follows the pattern shown in Fig. 13, which depicts the calculation of the VaR and CVaR. The VaR is the cut-off point dependent on the confidence level, α, attributed. The CVaR is the average of all scenarios above VaR, e.g., in a case of 100 scenarios with an α of 95%, the VaR would represent the cost of the fifth most expensive scenario, and the CVaR would be the average of the five most expensive scenarios.

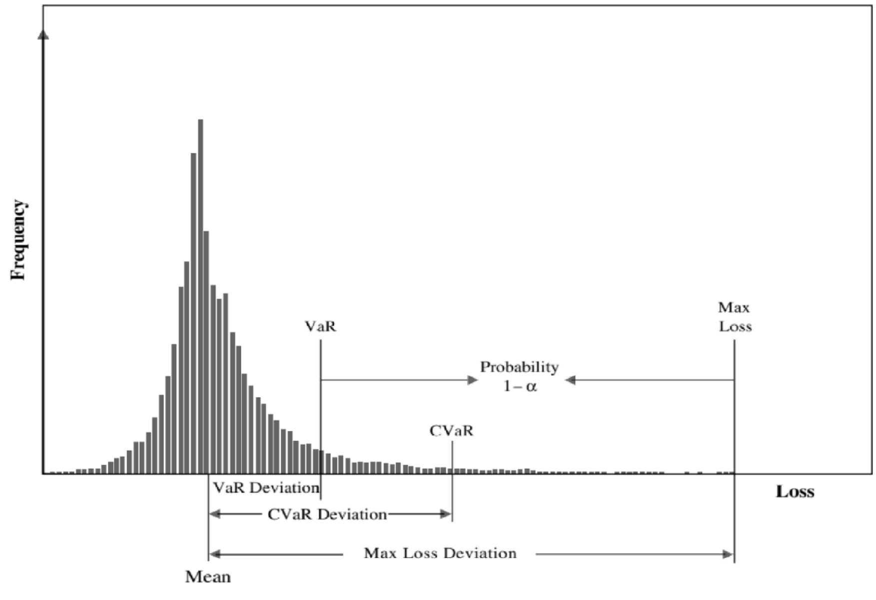

Figure 13 - VaR and CVaR calculation (Source: [73])

Xuan et al. in [59] proposed an integrated energy system, including energy storage and RES, to quantify and manage the risk brought on by operational uncertainty. The approach has two stages: planning for investments and optimizing operations. Bender's decomposition and the modified backward scenario reduction approach are used to solve the model. Although the findings demonstrate the model's effectiveness, the authors do not consider the necessity of remunerating DG, which is crucial because it accounts for a significant portion of the related expenses.

The same happens with Tekiner-Mogulkoc et al. in [60]. The approach solves the electricity-generation expansion planning problem, which involves deciding what types of power plants to build and when and where to build them under uncertain demand growth. The paper proposes two ways of incorporating risk-aversion into the problem, using CVaR and maximum regret as risk measures. The authors develop mathematical models and present numerical examples to show how the optimal expansion plans change when risk is considered.

Yang et al. in [61] apply CVaR to electric-heat-hydrogen energy systems through a weighted average of 135 scenarios. In [62], Xuan et al. integrate ESS into a network and implement CVaR to address the issues that modern networks accelerate, such as harder forecasting and lower flexibility. Li et al. in [63] provide a risk-averse adaptive stochastic technique to improve power and thermal energy microgrid operation.

In [64], Almeida et al. provide a risk-based energy resource management (ERM) strategy for aggregators in DNs with DER, considering VaR and CVaR evolutionary methods for optimization which are compared and evaluated. The results reveal that risk-averse methods can lower the worst situations' cost and impact. In Fig. 14, the evolution of scenario costs can be seen for different risk aversion levels, β, which corresponds to the pattern that will later be seen in this thesis' results. Fig. 14 shows that implementing CVaR reduces the costs of extreme scenarios while slightly increasing the other scenarios. This pattern is more severe the higher β is.

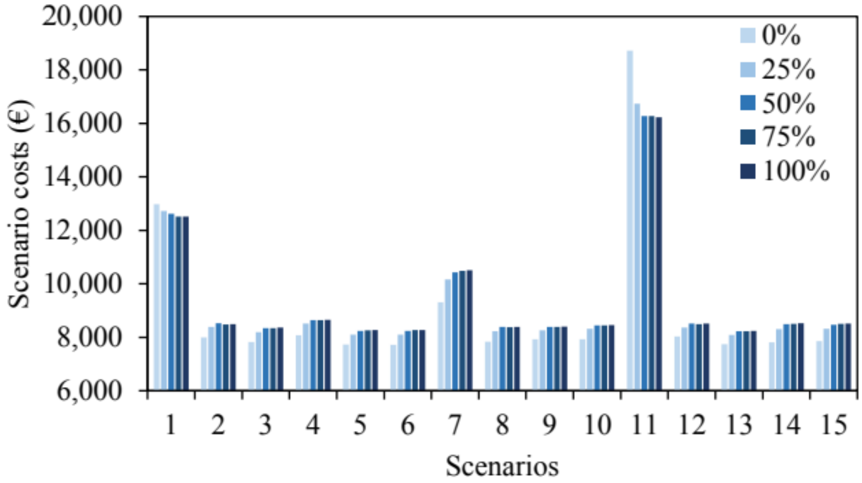

Figure 14 – Average scenario costs for multiple levels of risk aversion (Source: [64])

Khodabakhsh et al. [65] address the optimal control of energy storage in a microgrid by minimizing CVaR, subject to several uncertainties. The authors apply two different formulations, the first being a stochastic scenario-based approach and the second being the worst-case CVaR approach, by making the constraints robust.

Zhang et al. in [66] propose a method to assess the risk of extreme events, such as widespread blackouts caused by natural disasters or human attacks. The method combines the generalized extreme value theory and the CVaR measurement theory to model the distribution and measure the severity of power system losses under extreme conditions. The method is compared with the traditional risk assessment methods. The results show that the proposed method can capture the low-probability and high-impact risks the power system may face and provide helpful information for decision-makers.

Almeida et al. in [67] offer a risk-based optimization technique for an aggregator's centralized day-ahead ERM that controls several DER with unpredictable behavior. The study contrasts risk-neutral and risk-averse approaches, incorporating the CVaR method to consider severe occurrences. There is a study to frame the ERM issue as a stochastic MILP model and a metaheuristic was used to solve it, due to the problem size. The case study in the paper is based on a 13-bus DN with a high penetration of EVs and RES. The study demonstrates how a risk-averse strategy lowers worst-case scenario expenses while increasing day-to-day operational costs, resulting in safer and more reliable solutions from the model.

A mathematical model for planning the growth of a transmission network under demand uncertainty and risk aversion is presented in [68] by Delgado et al. The model minimizes both the projected total cost and the CVaR of the total cost (bi-objective MILP formulation). The three networks studied in this research work are independent, radial, and meshed. In addition to how several network designs balance the cost and risk, this work also assesses how network structure, demand fluctuation, demand correlation, and risk aversion impact the best possible investment choices.

To optimally plan the DN layout, [69] suggests a novel risk-based approach that considers demand uncertainty, energy price volatility, and failure rate and duration. The strategy reduces the cost of severe occurrences by utilizing the branch exchange technique and the CVaR indicator. The method is used to test a system with 52 load points and two substations, and the findings demonstrate that the risk-based approach may lower the cost of planning in the worst-case scenarios by roughly 10%. Table 12 also confirms what is shown in Fig. 14.

Table 12 - Costs in various cases of risk (Source: [69])

Cost component	Case 1 (Traditional)	Case 2 (Risk-based)
Investment	209,270	222,580
Maintenance	16,628	17,685
Losses (worst)	106,200	87,056
Reliability (worst)	401,760	375,340
Technical risk (worst)	75,900	10,980
Deterministic cost	345,800	346,770
Expected cost (C_{Ex})	382,430	371,950
C_{Ex} + $\text{CVaR}_{0.95}$	577,010	525,380
Worst scenario	809,750	713,640

Fu et al. [70] provide a statistical machine-learning model for stochastic optimal DN planning considering solar power and HVAC (Heating, Ventilation, and Air Conditioning) load uncertainties and correlations. The proposed approach models weather factors reduce stochastic variable dimension and scenario scale calculates probabilistic power flow, and solves the stochastic programming model using Markov chains, copula functions, nearest neighbor theory, nonnegative matrix decomposition, stochastic response surface method, and probabilistic inequality theory. Comparing the proposed technique to the scenario reduction algorithm and Monte Carlo method in a 33-bus distribution system proves its efficacy and efficiency.

The research work in [71] presents a two-stage MILP technique for optimizing multi-energy systems that include different energy sectors with distributed RES. The method improves equipment selection and connections by modeling a multi-energy system as a directed acyclic graph with numerous levels. The method can plan multi-energy systems from inception and expand them. A case study of a Beijing multi-energy system shows the approach's success.

Lastly, Lima et al. in [72] offer a model for the multi-period planning of electrical DN and EV charging stations, considering the risk of planning cost volatility and carbon emissions. The model integrates short- and long-term uncertainty linked to renewable generation, demand, energy price, carbon tax, and demand growth and employs CVaR as a risk metric. The model seeks to reduce the net present risk, operation, and investment cost. The model is solved as a two-stage MILP problem. Applying the model to two case studies demonstrates that the suggested strategy can produce more reliable and sustainable expansion plans.

2.7. CO_2 EMISSIONS

In continuation to all that has been said thus far, an obvious addition to any network planning study is considering the amount of emissions. This consideration ties into the introduction to topic 2.6. where it was mentioned that it is very rare for a model to include all relevant topics simultaneously (RES, ESS, uncertainty, remuneration of resources, risk aversion, etc.), it is even rarer to include CO_2 to that group. In Table 13, there is some relevant literature to this section of the work.

Table 13 – CO_2 emission on network planning literature

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[74]	Reinforcement of intermittent RES and capacitor banks	Minimization of power losses, enhancement of voltage stability and improvement of network security	Fuzzy decision-making criteria and Particle Swarm Optimization	Missing the remuneration of DG and consideration of extreme events
[75]	Distribution System Expansion Planning	Minimization of greenhouse gas emissions	Two-stage stochastic MICP	Not considering remuneration of DG, storages, and risk

Ref.	Focus	Main Objectives	Used Techniques	Limitations
[76]	Distribution System Expansion Planning	Minimization of investment and generation costs and CO_2 emissions	Multi-objective MILP formulation	The authors point not considering network reliability topics as a flaw
[77]	Optimal sizing and sizing of RES, ESS and reactive support devices considering CO_2	Minimization of cost of energy delivered and investment costs	MINLP formulation, linearized to MILP, solved using AMPL and CPLEX	Missing extreme events and remuneration of DG
[78]	Optimal allocation of EVP and RES including CO_2 emissions	Minimizing the costs of EVP and RES investment, operational costs, RES maintenance costs and CO_2 emission costs	MILP formulation	Not considering the uncertainty associated with the penetration of EVs and RES

Kayal et al. present a planning approach for integrating solar, wind, and capacitor banks in an electric power DN [74]. The model seeks to lower costs, losses, emissions, voltage stability, and network security. The model uses a multi-objective particle swarm optimization algorithm with fuzzy decision-making to find RES and capacitor units' optimal location and size on a 28-bus Indian rural DN. The results show that the proposed model outperforms single RES or capacitor units.

Home-Ortiz et al.'s stochastic mixed-integer convex programming model for long-term distribution system expansion planning accounts for greenhouse gas emissions and predicts the best substation reinforcement, conductor replacement for overloaded feeders, and renewable and dispatchable DG unit location and sizing [75]. The model accounts for wind generation power and electricity usage unpredictability. The model is tested under different scenarios on a 34-node distribution system and a 135-node real network. The model generates an economic investment plan that reduces DN carbon emissions.

Lima et al. in [76], provide a mathematical model for EDS expansion planning that balances cost and CO_2 reduction. Investments for renewable and non-renewable substations, circuits, and DG units are considered. Demand and renewable generation uncertainties are addressed using two-stage stochastic programming based on scenarios. The enhanced-constrained method generates Pareto optimum solutions for multi-objective problems. A 54-node distribution system case study shows the trade-off between the two objectives and how renewable DG affects expansion. The authors find that there is a correlation between a lower value of CO_2 emission costs and a higher total investment cost, as should be expected, seen in Fig. 15.

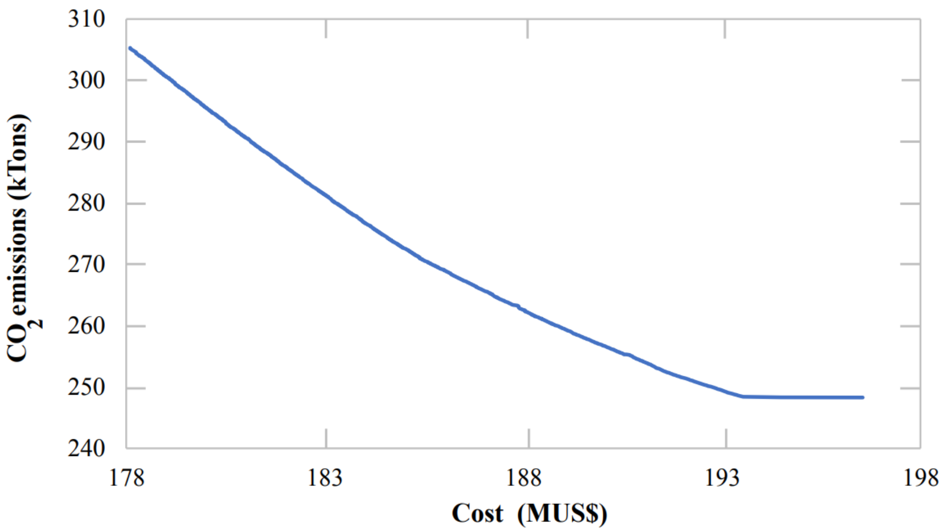

Figure 15 - Correlation between CO_2 emissions and total investment cost (Source: [76])

Melgar Dominguez et al. in [77] use a mathematical model to optimize EDS architecture by considering RES location and quantity, capacitor banks, and ESS. The idea reduces EDSs' energy, investment, and environmental impacts while improving their technical performance. The model adjusts for PV generating and consumption uncertainties using external uncertainty indexes. The mixed-integer nonlinear programming model is linearized and solved using commercial tools. The model saves money, improves voltage stability, and reduces emissions on a 135-node distribution system.

Lastly, Lima et al. in [78] describe a mathematical model for allocating electric vehicle charging stations (EVCSs) and RES in EDS. The model considers the uncertainties of traditional consumption, EV demand, renewable generation, and the environmental impact of CO_2 emissions. A commercial solver solves the model, written as a two-stage stochastic MILP problem. The results suggest that allocating EVCSs and RES can simultaneously minimize the EDS's total cost and CO_2 emissions. The paper also conducts sensitivity analysis with various CO_2 emission rates and levels of EV adoption.

Once again, the same point of Fig. 15 is proven in Table 14 by the authors.

Table 14 - Evolution of CO_2 emissions vs total costs vs RES investments (Source: [78])

Solution	Total cost (millions of USD)	CO_2 emissions (ktons)	RES Investments (millions of USD)
1	131.98	506.30	20.34
2	132.03	503.22	21.10
3	133.28	499.75	22.15
4	134.75	496.49	23.37
5	138.41	493.21	24.80
6	141.42	489.97	26.56
7	143.29	486.72	29.18
8	146.43	483.45	33.07
9	151.25	480.20	45.64

2.8. CHAPTER CONCLUSIONS

This chapter displayed the importance and necessity of optimal planning when it comes to DNs. This importance has been severely accentuated in recent times since the ever-increasing penetration of RES ends up being a catalyst for both lower flexibility and harder forecasting of networks. Optimal planning mitigates these issues to the best possible degree, and in later years, the prominent introduction of both uncertainties and ESSs on networks has worked to an extent. As shown in the reviewed literature, there are many ways of formulating and solving an optimization problem regarding power distribution network, from the two-stage stochastic model to the standard deterministic one. It has also been shown that there is an ever-present worry about optimally allocating of energy storage systems to aid the network.

Furthermore, a wide variety of uncertainty types have been showcased, from wind and solar irradiance to urbanity to the present seasonal uncertainty, there is a large range of topics to discuss when it comes to uncertainty. The common consensus seems to be that future work related to network planning should include ESSs and all possible uncertainty to allow for the best possible solution, which will be harder and harder to achieve since the increase in RES penetration is not slowing down any time soon. As mentioned before-hand considering remuneration of resources is also a must since it accounts for a major portion of associated network costs. The consideration for risk aversion is also an important study since it mitigates otherwise extreme events. Even if the total planning cost is slightly worse when considering risk aversion, the network is much better prepared for the situation if an extreme event occurs, reducing the resulting costs significantly. Finally, considering actual associated values related to carbon emissions is also necessary since the focal point of this movement toward more RES penetration is carbon neutrality. By minimizing carbon emissions, consideration for that factor is assured.

3. PROPOSED METHODOLOGY

This section provides an overview of the model's definition and application. Subsection 3.1. outlines all the considered scenarios, how they were defined, and how they are distinguished. Subsection 3.2. shows how the uncertainty was applied to each scenario, with varying PV and Wind generation and load levels. Subsection 3.3. showcases the definition of remuneration values to apply to each generation of technology. Subsection 3.4. outlines some decisions and processes used for risk consideration through VaR and CVaR. Subsection 3.5. addresses the considerations regarding carbon emissions. Subsection 3.6. outlines the entire optimization model. Lastly, Subsection 3.7. showcases the economic analysis applied to the chosen case studies.

3.1. SCENARIO CREATION

The model, which is a two-stage stochastic model, handles 8760 different scenarios, being the hourly values, themselves separated into 16 main situational scenarios (as shown in Fig. 12). The hourly distribution of the main situational scenarios is as follows in Table 15.

Table 15-Scenario segmentation by hours and probability

Season	Season Days	Hours/Season (h)				Scenario Probability			
		Morning	Peak	Afternoon	Night	Morning	Peak	Afternoon	Night
Summer	92	644	276	276	1012	7.35% *(1)**	3.15% *(2)*	3.15% *(3)*	11.55% *(4)*
Spring	92	460	276	368	1104	5.25% *(5)*	3.15% *(6)*	4.20% *(7)*	12.60% *(8)*
Fall	91	455	182	273	1274	5.19% *(9)*	2.08% *(10)*	3.12% *(11)*	14.54% *(12)*
Winter	90	360	180	270	1350	4.11% *(13)*	2.05% *(14)*	3.08% *(15)*	15.41% *(16)*

* From here on onwards, every mention of "scenario *(1)*" refers to the situation of "summer morning". Same applies to every other main scenario, as shown in Table 15. For further clarification, main scenario *(10)* ("fall peak"), i.e., has 182 individual hourly scenarios. While the probabilities and considerations remain unchanged through the whole thesis, for case studies 4 and 5, the order of these main scenarios are changed, following what is shown later in Table 31.

The chance of the situational scenario of Summer Morning (scenario 1) would be determined as follows in equation (1) to provide even more insight on how the likelihood of each scenario occurring is calculated:

$$Prob_{Summ_{Morn}} = \frac{644}{8760} \cdot 100\% \tag{1}$$

For the most accurate simulation of a real-world situation, 50 000 initial scenarios were generated for each of the 16 initial main seasonal scenarios. These scenarios yield DG (PV and wind) values, load values, EV state values, and storage unit states. In order to match the hourly uncertainty value, these 50 000 scenarios are passed through a scenario reduction tool, which has been shown to conserve computational resources without sacrificing efficacy [79], [80]. As an explanation, for instance, the initial 50 000 summer morning scenarios are reduced to 644, each with a corresponding probability of occurrence. The probability of each of the 8760 final scenarios is represented by equation (2).

$$P_{final} = P_{MainScenP} \cdot P_{IndividualScenP} \tag{2}$$

Where P_{final} ends up being the final probability of the entire scenario, $P_{MainScenP}$ is the probability of the main seasonal scenario (7.35% for summer morning, for example), and $P_{IndiviudalScenP}$, which is the probability of each of the 8760 sub-scenarios occurring within the initial main seasonal scenario.

Only case studies 4 and 5 (Later shown in chapter 4.1. as the study of risk aversion through CVaR and CO_2 emissions, respectively) do not follow this number of scenarios due to issues with computational tractability. Instead, those two case studies are reduced to a total of four sub-scenarios per each main scenario, totaling 64 sub-scenarios, e.g., Summer Morning does not have the initial 50 000 scenarios to 644, but to 4 instead. Again, this applies to case studies 4 and 5 (Risk and CO_2 emissions).

As for the specific details of the scenario creation, it follows Fig. 16, which illustrates all the steps to determine the values for all scenarios. These scenarios are created through the Monte-Carlo method.

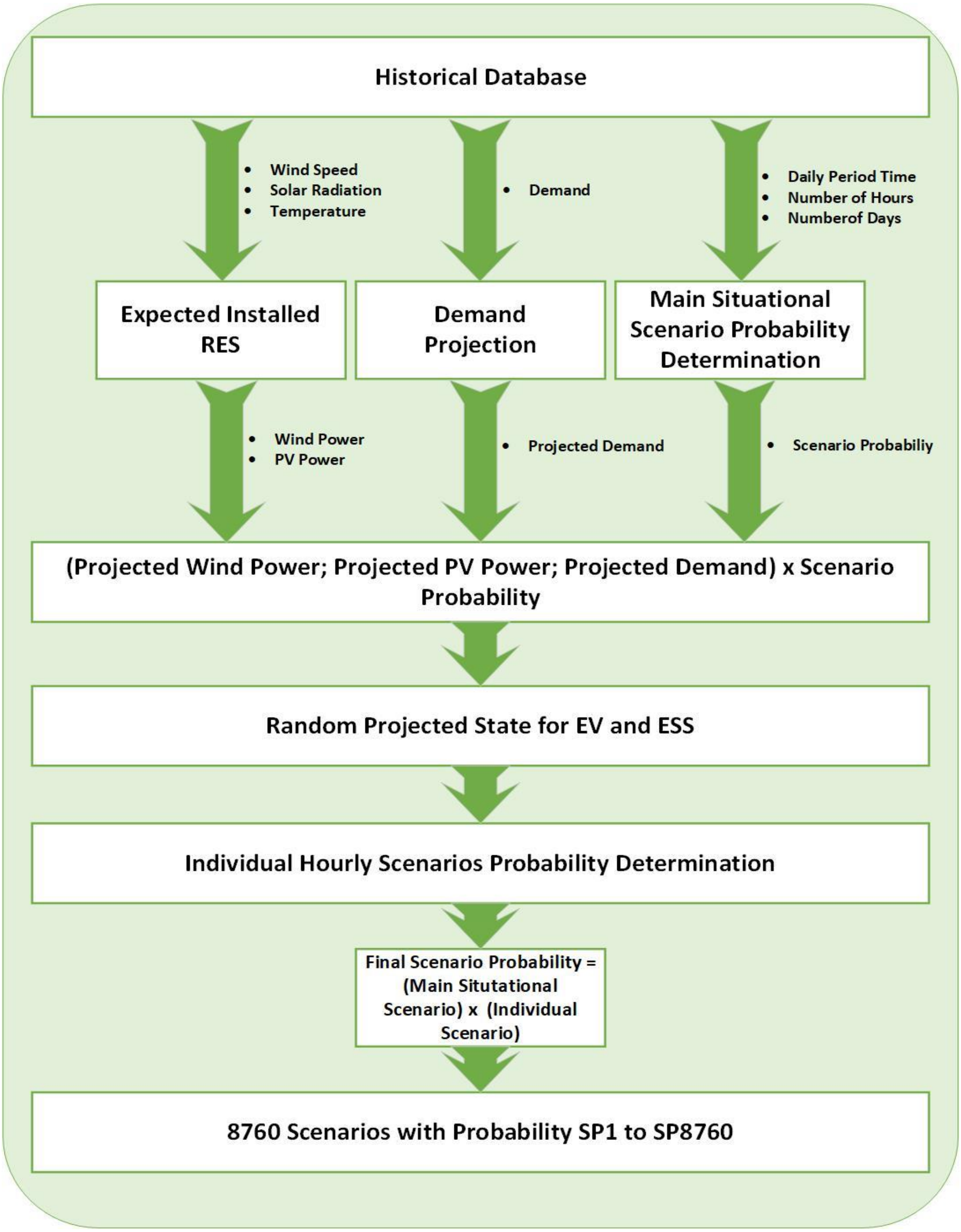

Figure 16 – Scenario diagram creation (Adapted from [1])

3.2. Uncertainty Application

To directly apply uncertainty to the hourly defined scenarios, data were collected and analyzed from 2017 to 2022 in Portugal to best characterize the behavior of PV and Wind generation and load, resulting in a multiplicative factor for each of the 16 main situational scenarios to differentiate them. The load data was extracted from [81], and the PV and Wind behavior data was extracted from [82]. All the resulting load and generation factors for PV and Wind energy are listed in Table 16. The spring morning scenario was regarded as the baseline (unitary value for PV/Wind/Load) to enable direct comparisons between the main situational scenarios (1 to 16). All other multiplicative factors are found through a comparison with this spring morning situation.

Table 16 – Found multiplicative factor for PV/Wind/Load for all scenarios

Season	Multiplicative Factor for PV/Wind/Load			
	Morning	Peak	Afternoon	Night
Summer	1.40 / 1.00 / 0.99	3.20 / 1.60 / 1.11	2.40 / 1.00 / 0.91	0.05 / 0.80 / 0.59
Spring	1.00 / 1.00 / 1.00	2.60 / 1.40 / 1.12	1.40 / 1.00 / 0.92	0.05 / 0.80 / 0.65
Fall	1.00 / 1.00 / 1.03	2.20 / 1.40 / 1.16	1.40 / 1.00 / 0.93	0.05 / 0.80 / 0.65
Winter	0.60 / 1.00 / 1.03	1.40 / 1.40 / 1.14	1.00 / 1.00 / 0.95	0.05 / 0.80 / 0.69

These factors are applied directly to the scenario creation, and for EVs, it was considered that the state was independent of the seasonal time. The scenarios only carry the randomness of the scenario creation without any uncertainty specific to each season and/or timeslot.

3.3. REMUNERATION VALUES OF DISTRIBUTED RESOURCES

Regarding the remuneration of distributed resources, this study was conducted to discover the most accurate pricing feasible for each technology, and the data for this study was obtained from various sources [83]–[90]. A price was determined for the typical use of all technologies, and another price, dubbed the "Excess Price," was established for any surplus energy that was generated but not put to use. Table 17 demonstrates how the final expenses were defined. The proposed cost of 300 m.u./MWh follows the study made in [1], where an analysis was made for the values of 100, 200, 300, 400 and 500 m.u./MWh, and 300 was found to be the most suitable. A study was be done to understand the impact of ESSs on total remuneration.

A detailed explanation of the studied network is presented in the following chapter ("3.6. Optimization Model"). Still, it should be clarified as of now that the network used in this study has PV, Wind, Biomass, and a Substation as generation sources. The PV and Wind generators are assumed to be owned by network participants, which need individual remuneration. The Biomass and Substation are assumed to be owned by the DSO, meaning they are dispatchable at will. Two ESSs are in the network (Buses 31/87), part of a contracted agreement between the DSO and its owner. The contract indicates that the DSO has extremely cheap access to the energy stored in these devices as long as they do not access more than 25% of its current capacity. If the DSO needs more than 25%, that would represent a breach of contract, meaning there would be a penalty to the DSO and a heavy price for ESS usage. The model may allow for installing more ESSs if it is needed, but it is considered that the DSO owns the unit.

Table 17 - Prices of each technology to remunerate accordingly.

Generation Source	**Regular Usage Price (m.u./ MWh)**	**Excessive Generation Price (m.u./MWh)**
Owned and Operated by the DSO		
Substation	55	300
Biomass	45	300
*ESS**	40	400
Owned and Operated by another Party, which needs compensation from the DSO		
Wind Farms	45	150
PV Parks	45	150
ESS (Buses 31/87, within Contract)	30	150
ESS (Buses 31/87, breach of Contract)	400	1000

***Any ESS that the model decides to install apart from the two that were already in place (buses 31/87) are assumed to be owned by the DSO**

3.4. CVaR and VaR Specifications

As mentioned in chapter 3.1., the study that analyzes the impacts of risk assessment through CVaR (case study 4) only considers a total of 64 sub-scenarios.

There are a total of six variations for the 64 sub-scenarios included in the study. The parameter α (the confidence level) takes values of 99%, 95%, and 90%. The parameter β (risk aversion) takes values of 0 and 1, meaning the model will be analyzed as risk-neutral and risk-averse. When considering a risk-averse approach, the following is done:

- Sort the sub-scenarios in ascending order of total cost;
- Calculate the α percentile position, $\alpha_{PercPos}$, through equation (3);

$$\alpha_{PercPos} = \alpha \cdot Ns \tag{3}$$

- Find the VaR as the total cost of $\alpha_{PercPos}$;
- Calculate the CVaR as the average of all sub-scenarios costlier than the sub-scenario $\alpha_{PercPos}$.

The study considers events of extreme impact on the network but with a low probability of occurrence. Five extreme sub-scenarios were implemented, following Fig. 17.

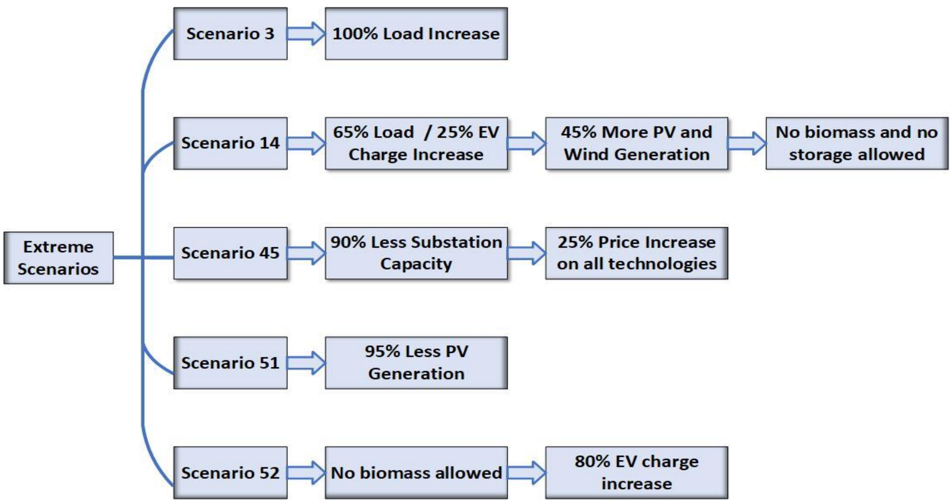

Figure 17 - Description of the considered extreme sub-scenarios

3.5. CARBON EMISSION SPECIFICATIONS

One important aspect to consider in modern society is carbon emission, which needs to be reduced to meet the EU's requirement of 40% RES penetration by 2030 [5].

Regarding some considerations for the carbon emissions (applied in Case Study 5), the values seen in Table 18 are the emission rates of each generation technology, which was found as an average of [91], [92], and the emission costs, which is 51 m.u./ton, the official social cost of carbon in the United States of America [93].

Table 18 - Emission rates of each technology and costs of emission - Case study 5

	PV	Wind	ESS	Biomass	Substation
Emission Rate (tons/MWh)	0.0584	0.0276	0.2012	0.7550	0.6079
Costs of Emission (m.u./ton)	51				

3.6. OPTIMIZATION MODEL

As previously mentioned, the model is a two-stage stochastic model. The model allows for investments in potential new lines (feeders and the respective transformers), a reconfiguration of its topology, and investments in ESSs. There is an analysis for the project's lifetime cycle of 30 years. The aim is also to ensure a radial topology.

The model's solution outputs the following information:

- Every associated cost: New Lines, Maintenance of Lines, Expected Energy Not Supplied (EENS), Power Losses, ESS Installation and Maintenance, Load Cut;
- Amount of needed generation from the DSO's side (Substation, Biomass, and potentially ESS);
- Optimal Power Flow (OPF) for each line in every scenario;
- System Average Interruption Duration Index (SAIDI);
- System Average Interruption Frequency Index (SAIFI);
- Excessive generation of DG;
- Location and size of ESS;
- Optimal network topology;

- Cost for generation to the DSO (Substation, Biomass, partially ESS) yearly and for the entire 30-year period;

- Value to compensate to the network contributors (PV, Wind, and partially ESS), also yearly and for the entire 30 years;

- CO_2 emissions and costs (Case Study 5 only);

- Economic analysis compared to the initial network.

The initial network configuration with the potential new lines, DG, ESS, and Electric Vehicle Parking lot (EVP), is shown in Fig. 18. The model allows itself to choose between two line types and two ESS types for each unit chosen (More details in 4.1. Case Studies' Definition).

Later, in chapter 4.1., the differences in the optimization model between all case studies are to be explained. The model portrayed in this chapter (3.6.) is the full model.

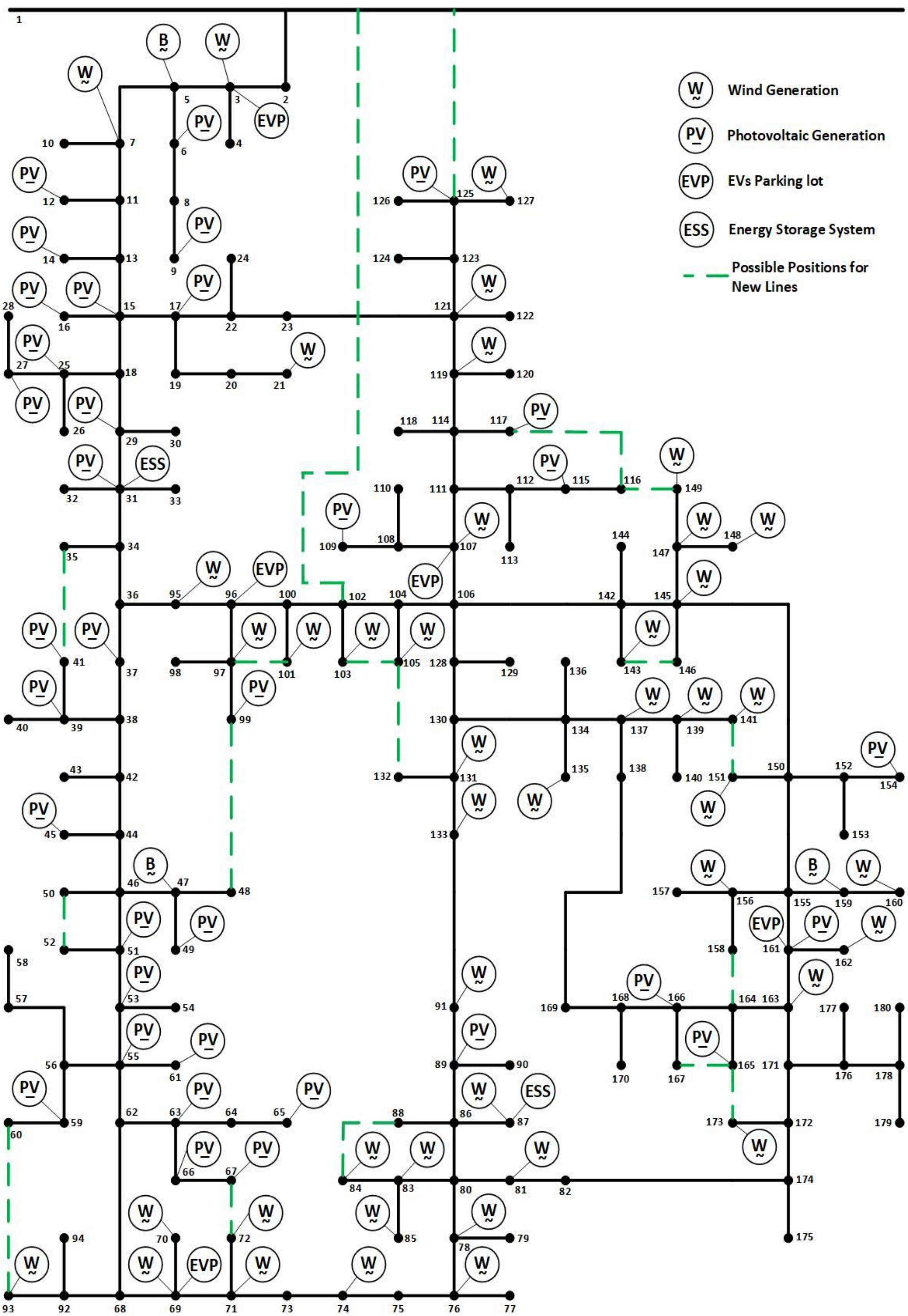

Figure 18 - Initial network configuration with potential new lines (Adapted from [1])

3.6.1. OBJECTIVE FUNCTION

The objective function of the model follows equations (3) – (7), aiming to minimize the total planning cost.

Equation (3) represents all the components that make the objective function.

$$Minimize PC = PC_1 + PC_2 + PC_{CO2} + FT_{risk} \tag{3}$$

Here, PC_1 represents the stochastic model's first stage, represented in equation (4).

$$
\begin{array}{ll}
PC_1 = \left[\begin{array}{l}
\sum_{i\in\Omega_B}\sum_{j\in\Omega_B}\sum_{c\in\Omega_O} y_{(i,j,c)} \cdot LineCost_{(i,j,c)} + \\
\sum_{i\in\Omega_B}\sum_{j\in\Omega_B}\sum_{c\in\Omega_O} y_{(i,j,c)} \cdot LineMCost_{(i,j,c)} + \\
\sum_{u\in\Omega_{STO}} a_{(e,u)} \cdot StCost_u + \\
\sum_{u\in\Omega_{STO}} a_{(e,u)} \cdot StMCost_u
\end{array}\right] &
\begin{array}{l}
\text{Lines Cost} \\
\text{Lines Maintenance} \\
\text{ESS investment} \\
\text{ESS maintenance}
\end{array}
\end{array} \tag{4}
$$

PC_2 represents the stochastic model's second stage, as shown in equation (5).

$$
\begin{array}{ll}
PC_2 = \sum_{s\in\Omega_S}\left[\left(\begin{array}{l}
\left(\sum_{i\in\Omega_B}\sum_{c\in\Omega_O} Flow_{(i,j,c,s)} \cdot FOR_{(i,j,c)}\right) \cdot ENSCost + \\
\left(\sum_{i\in\Omega_B}\sum_{c\in\Omega_O} Flow_{(i,j,c,s)} \cdot LF_{(i,j,c)}\right) \cdot LossC + \\
\sum_{g\in\Omega_{DG}^{nd}} P_{PGC(g,s)} \cdot PCost_{PGC(g)} + \\
\sum_{lo\in\Omega_L^b} P_{LoadCut(lo,s)} \cdot CutCost_{lo} + \\
\boxed{\begin{array}{l}
\sum_{bs\in BS} p_{Sub(s)} \cdot Sub_{Price} + \sum_{bio\in Bio} p_{Bio(bio,s)} \cdot Bio_{Price} + \\
\sum_{pv\in PV} p_{PV(pv,s)} \cdot PV_{Price} + \sum_{wi\in WI} p_{WI(wi,s)} \cdot WI_{Price}
\end{array}}
\end{array}\right) \cdot \omega_s\right] &
\begin{array}{l}
\text{Energy Not Supplied} \\
\text{Power Losses} \\
\text{Generation Curtailment} \\
\text{Load Curtailment} \\
\text{Remuneration of Resources}
\end{array}
\end{array} \tag{5}
$$

PC_{CO2} represents the consideration for CO_2 emissions in the model, shown in equation (6).

$$PC_{CO2} = \sum_{s\in\Omega_S}\left[\left(\begin{array}{l} p_{Sub(bs)}\cdot\iota_{bs} + \sum_{bio\in Bio} p_{Bio(bio,s)}\cdot\iota_{Bio} + \\ \sum_{pv\in PV} p_{\mathrm{PV(pv},s)}\cdot\iota_{PV} + \sum_{wi\in WI} p_{WI(wi,s)}\cdot\iota_{WI} + \\ +\sum_{e\in E} p_{\mathrm{storage(e,u},s)}\cdot\iota_E \end{array}\right)\cdot\varpi_s\cdot EC_{CO_2}\right] \tag{6}$$

The third part of the objective function represents the consideration for risk aversion, implemented through CVaR, as shown in equation (7). This constraint follows the methods proven in [94], [95].

$$FT_{risk} = \left(\left(1-\beta\right)\cdot t_c\right)+\beta\cdot C_{VaR_\alpha} \tag{7}$$

Every indice, set, parameter, and variable are detailed in the Nomenclature section at the beginning of the document. In this objective function, the FOR, which is the forced outage rate, is calculated as follows in equation (8):

$$FOR_{(i,j,c)} = \frac{\lambda_{(i,j,c)}\cdot r_{(i,j,c)}}{8760 - r_{(i,j,c)}} \tag{8}$$

3.6.2. MODEL CONSTRAINTS

The model is subject to technical constraints (9)-(33). Constraints explained from 3.6.2.1. to 3.6.2.6. represent the network-specific constraints. Constraints in 3.6.2.7. and 3.6.2.8. correspond to imposed limits to the generation amount from the DSO's side (Substation and Biomass). Constraints in 3.6.2.9. to 3.6.2.15. are related to the ESSs. Constraint 3.6.2.16. relates to EVs. The reliability indexes SAIDI and SAIFI are addressed in 3.6.2.17. and 3.6.2.18., respectively. Lastly 3.6.2.19. and 3.6.2.20 represent the curtailment constraints.

3.6.2.1. POWER BALANCE

There is an obligation to ensure that the total amount of generated energy equals the demand. Equation (9) represents the entire constraint, divided into (9.A) through to (9.I).

$$\overset{A}{\boxed{\sum_{i\in\Omega_{DG}^{nd}}\left(p_{DG(i,s)}-p_{PGC(i,s)}\right)}}+\overset{B}{\boxed{\sum_{i\in\Omega_{BS}^{b}}p_{Sub(i)}+\sum_{bio\in\Omega_{Bio}^{b}}P_{Bio(bio,s)}}}+\overset{C}{\boxed{\sum_{i\in\Omega_{L}^{b}}p_{LoadCut(i,s)}}}-$$
$$\overset{D}{\boxed{\sum_{i\in\Omega_{L}^{b}}p_{Load(i,s)}}}\overset{E}{\boxed{-\sum_{i\in\Omega_{E}^{b}}\sum_{i\in\Omega_{E}}p_{storage(i,u,s)}}}\overset{F}{\boxed{-\sum_{i\in\Omega_{V}^{b}}EVP_{(i)}}}\overset{G}{\boxed{-\sum_{i\in\Omega_{B}}\sum_{c\in\Omega_{O}}\left(Flow_{(i,j,c,s)}\cdot LF_{(i,j,c)}\right)}}+$$
$$\overset{H}{\boxed{\sum_{i\in\Omega_{B}}\sum_{c\in\Omega_{O}}Flow_{(i,j,c,s)}}}\overset{I}{\boxed{-\sum_{i\in\Omega_{B}}\sum_{c\in\Omega_{O}}Flow_{(j,i,c,s)}}}=0 \tag{9}$$

$$\forall_{s}\in\Omega_{S},\forall_{j}\in\Omega_{B}$$

Where:

(9.A) → Renewable generation;

(9.B) → Power provided by the DSO;

(9.C) → Load curtailment;

(9.D) → Load demand;

(9.E) → ESS charge/discharge;

(9.F) → Charge from EVP;

(9.G) → Power losses;

(9.H) → Flow into bus *j* from bus *i*;

(9.I) → Flow into bus *i* from bus *j*.

The entire equation must equal zero, meaning all energy is accounted for.

3.6.2.2. Maximum permitted flow for each line

A maximum cap for power flow in each line is needed, and it is represented by (10).

$$\begin{gathered}0\leq Flow_{(i,j,c,s)}\leq Flow_{(i,j,c)}^{\max}\cdot y_{(i,j,c)}\\ \forall_{S}\in\Omega_{s},\forall_{Y}\in\{0,1\},\forall(i,j,c)\in\Omega_{l}\end{gathered} \tag{10}$$

The thermal capacity of the line itself most impacts this.

3.6.2.3. Unidirectional Power Flow

At any given time, there cannot be power flowing from bus *i* to *j*, and *j* to *i* simultaneously, so there must be a constraint to guarantee unidirectional power flow, at any given time, which is represented in constraint (11).

$$
\begin{aligned}
& y_{(i,j,c)} + y_{(j,i,c)} \leq 1 \\
& \forall_{Y} \in \{0,1\}, \forall (i,j,c) \in \Omega_{l}
\end{aligned}
\tag{11}
$$

3.6.2.4. Radial Topology

Since there is an aim for a radial topology in the model, constraint (12) is implemented, which ensures that all buses, *j*, only have one line entering them at any given time, guaranteeing that the network is indeed radial.

$$
\begin{aligned}
& \sum_{j \in \Omega_{L}^{b}} \sum_{c \in \Omega_{O}} y_{(i,j,c)} = 1 \\
& y \in \{0,1\}, \forall (i) \in \Omega_{B}
\end{aligned}
\tag{12}
$$

3.6.2.5. Avoiding Island Creation

This specific set of constraints (13)-(16) is necessary, especially on networks heavily penetrated by DG, to ensure that there are no islands within the network that are only fed by the DG within the island, essentially demanding that there is a direct connection from any chosen bus to the substation. This was achieved through a method of creating a fictitious flow to feed a fictitious load, without the use of DG, only using the substation, ensuring that all buses are connected to it. Creating this constraint is not always mandatory, and if any network planner decides that it is preferable to permit islands, this constraint is ignorable. Usually, however, avoiding islands is preferable, as shown in [96].

$$
\begin{aligned}
& \sum_{i \in \Omega_{B}} \sum_{j \in \Omega_{B}} \sum_{c \in \Omega_{O}} d_{(i,j,c)} - \sum_{i \in \Omega_{B}} \sum_{j \in \Omega_{B}} \sum_{c \in \Omega_{O}} d_{(j,i,c)} = D_{(g)} \\
& \forall_{g} \in \Omega_{DG}
\end{aligned}
\tag{13}
$$

$$D_{(g)} = 1 \qquad \forall_g \in \Omega_{DG} \tag{14}$$

$$D_{(g)} = 0 \qquad \forall_g \notin \Omega_{DG} \cup \Omega_{BS} \tag{15}$$

$$\begin{gathered} | d_{(i,j,c)} | \leq nDG \cdot y_{(i,j,c)} \\ \forall (i,j,c) \in \Omega_l \end{gathered} \tag{16}$$

3.6.2.6. ONLY ONE LINE TYPE

Since the model is allowed to choose between two line types, constraint (17) is applied to guarantee that only one type (*c*) is chosen.

$$\begin{gathered} \sum_{c \in \Omega_O} y_{(i,j,c)} \leq 1 \\ \forall y \in \{0,1\}; \forall (i,j,c) \in \Omega_l \end{gathered} \tag{17}$$

3.6.2.7. MINIMUM AND MAXIMUM ADMISSIBLE GENERATION FOR SUBSTATION

The substation is limited to its maximum capacity, which is imposed by constraint (18).

$$0 \leq p_{Sub(bs)} \leq P_{SMaxLimit(bs)} \tag{18}$$

3.6.2.8. MINIMUM AND MAXIMUM ADMISSIBLE GENERATION FOR BIOMASS GENERATORS

Similarly, biomass generators are also limited to their maximum capacity, which is imposed by constraint (19). This maximum value is 0.25MW for each biomass generator (a detailed explanation can be found in 4. Case Study).

$$\begin{gathered} 0 \leq p_{Bio(b)} \leq P_{BioMaxLimit(b)} \\ \forall b \in \Omega_B \end{gathered} \tag{19}$$

3.6.2.9. ENERGY STORAGE SYSTEM CHARGING LIMITED TO MAXIMUM CAPACITY

Every ESS present in the network can only be charged up to its maximum capacity, considering the respective charging efficiency (20).

$$p_{storage(e,u,s)} \leq \frac{stCap_{(e,u)}}{cef \cdot \Delta t_{(s)}} \qquad (20)$$
$$\forall_e \in \Omega_E^b, \forall_u \in \Omega_E, \forall_s \in \Omega_S$$

3.6.2.10. ENERGY STORAGE SYSTEM DISCHARGING LIMITED TO MAXIMUM CAPACITY

Like the previous constraint, this imposes that, if the ESS feeds the network, it cannot discharge more than its maximum current capacity, according to its discharging efficiency (21).

$$p_{storage(e,u,s)} \geq \frac{-stCap_{(e,u)}}{def \cdot \Delta t_{(s)}} \qquad (21)$$
$$\forall_e \in \Omega_E^b, \forall_u \in \Omega_E, \forall_s \in \Omega_S$$

3.6.2.11. LIMITED ENERGY STORAGE SYSTEM CHARGE RATE

Consideration must be given to the rate at which an ESS can charge and discharge within a specific time frame. The ESS should be controlled to ensure that it operates within realistic limits, with charging and discharging occurring in incremental steps rather than in bulk. To enforce these requirements, constraints (22) and (23) are implemented.

$$p_{storage(e,u,s)} \leq stRate_{(e,u)} \cdot a_{(e,u)} \qquad (22)$$
$$\forall_a \in \{0,1\}, \forall_e \in \Omega_E^b, \forall_u \in \Omega_E, \forall_s \in \Omega_S$$

3.6.2.12. LIMITED ENERGY STORAGE SYSTEM DISCHARGE RATE

$$p_{storage(e,u,s)} \geq -stRate_{(e,u)} \cdot a_{(e,u)} \qquad (23)$$
$$\forall_a \in \{0,1\}, \forall_e \in \Omega_E^b, \forall_u \in \Omega_E, \forall_s \in \Omega_S$$

3.6.2.13. ONLY ONE ESS TYPE

As previously mentioned, the proposed model allows for a choice between two types of ESSs. There can only be one type of ESS chosen, which is what constraint (24) achieves.

$$\sum_{u\in\Omega_E} a_{(e,u)} \leq 1 \qquad (24)$$
$$\forall_a \in \{0,1\}, \forall_e \in \Omega_E^b$$

3.6.2.14. PRICE ACCORDING TO ESS CONTRACT STATE – IN CONTRACT

As stated in topic 3.3. the currently installed ESSs are part of a contract from a third party with the DSO. Equation (25) guarantees that the price to apply to the amount of energy used by (or from) the ESS is adequately priced according to the contract in the situation that the DSO does not breach the 25% limit. $St_{PriceInContract}$ adequately follows the values stated in Table 17.

$$P_{storage(e,s)} \leq St_{Cap(e,u)} \cdot 0.25$$
$$St_{\mathrm{Cos}t(e,s)} = St_{PriceInContract} \cdot P_{storage(e,s)} \qquad (25)$$
$$\forall_e \in \Omega_E, \forall_s \in \Omega_S$$

3.6.2.15. PRICE ACCORDING TO ESS CONTRACT STATE – OUT OF CONTRACT

Regarding $St_{PriceOutOfContract}$, it is also detailed in Table 17 and refers to the price to be applied to the excess value of the accessed percentage of the ESS. If the DSO were to access 37% of the ESS maximum capacity, the initial 25% would still be remunerated according to the contracted price, and the remaining 12% would be remunerated according to the agreed contract breach amount. Equation (26) depicts exactly the described.

$$P_{\mathrm{Storage}(e,s)} \geq St_{Cap(e,u)} \cdot 0.25$$
$$St_{\mathrm{Cos}t(e,s)} = St_{PriceInContract} \cdot \left(St_{Cap(e,u)} \cdot 0.25\right) + St_{\mathrm{Pr}iceOutOfContract} \cdot \qquad (26)$$
$$\left(P_{\mathrm{Storage}(e,s)} - \left(St_{MaxCap(e)} \cdot 0.25\right)\right)$$

$$\forall_e \in \Omega_E, \forall_s \in \Omega_S$$

3.6.2.16. ELECTRIC VEHICLE PARKING LOTS CAPACITY

The studied network has five EVPs. Constraint (27) aims to limit the demand from each EVP to a maximum value. There is also a consideration for the simultaneity factor (*sf*).

$$p_{Charge(v,s)} = P_{ChargeLimit(v,s)} \cdot sf_v \qquad \forall_v \in \Omega_V^b, \forall_s \in \Omega_S \tag{27}$$

3.6.2.17. RELIABILITY INDEXES - SAIDI

One of the proposed goals was to reduce the original network's SAIDI and SAIFI. Equation (28) shows how SAIDI was calculated, and constraint (29) shows how it is limited. SAIDI is a metric for (hour/customers).

$$SAIDI = \frac{\sum_{i \in \Omega_L^b} Up_{(i)} \cdot N_{(i)}}{\sum_{i \in \Omega_L^b} N_{(i)}} \tag{28}$$

$$0 \leq SAIDI \leq SAIDI^{\max} \tag{29}$$

3.6.2.18. RELIABILITY INDEXES – SAIFI

The same thing occurs for the SAIFI index in equations (30) and (31), measuring (interruptions/customer).

$$SAIFI = \frac{\sum_{i \in \Omega_L^b} \lambda p_{(i)} \cdot N_{(i)}}{\sum_{i \in \Omega_L^b} N_{(i)}} \tag{30}$$

$$0 \leq SAIFI \leq SAIFI^{\max} \tag{31}$$

3.6.2.19. POWER GENERATION CURTAILMENT

Power generation curtailment refers to the amount of energy that is generated that does not end up being used. Naturally, there is a need to limit this value to being lower than the amount produced by any DG, *g*, in any scenario, *s* (32).

$$0 \leq p_{PGC(g,s)} \leq P_{DGScenario(g,s)}$$
$$\forall g \in \Omega_{DG}^{nd}, \forall s \in \Omega_S \qquad (32)$$

3.6.2.20. LOAD CURTAILMENT

Load curtailment refers to the amount of load demanded but not met. This value also cannot be higher than the demanded load, *lo*, in any given scenario *s*, (33).

$$0 \leq p_{LoadCut(lo,s)} \leq P_{Load(lo,s)}$$
$$\forall lo \in \Omega_L^b, \forall s \in \Omega_S \qquad (33)$$

3.7. ECONOMIC ANALYSIS

The proposed methodology includes an economic analysis, which aims to assess the study's interest by evaluating the following economic indicators: Net Present Value (NPV), Payback, and Internal Rate of Return (IRR). This analysis compares the considered case studies to the original network. The calculations follow [1], [97], [98].

The NPV calculation is represented by equation (34), Payback (35), and IRR (36).

$$NPV = \left(\sum_{t=1}^{n} \frac{NetCashInflow_t}{(1+r)^t} \right) - Initial_{Investment}$$
$$NPV = Savings - Investment \qquad (34)$$
$$NPV > 0$$

Where it is considered that '*t*' is the current time in '*n*' years, previously mentioned to be 30 years, '*r*' represents the discount rate divided by 100. The discount rate (0.05%) follows [99], [100], leading to a Capital Recovery Factor (CRF) of 0.034. CRF is calculated following (37), which is based on [101], [102].

$$Payback = \frac{TotalProject\,\mathrm{Cos}\,t}{AnnualCashInflows} \qquad (35)$$

$$IRR = \sum_{t-1}^{t} \frac{NetCashInflow_t}{(1+r)^t} - Initial_{Investment} \tag{36}$$

$$CRF = \frac{t \cdot (1+t) \cdot n}{(1+t) \cdot n - 1} \tag{37}$$

3.8. CHAPTER CONCLUSIONS

This chapter served as a display of some specifications and considerations regarding the work being developed. The definitions and decisions associated with aspects such as uncertainty, the costs associated with remuneration of distributed resources, the considerations proposed for extreme situations regarding risk aversion, and the emission rates of generation technologies are all important aspects that affect the entire study and the results output by the model. In this way, they require proper attention and research.

The optimization model was also outlined in this chapter, which was later adapted to Python, building it with Pyomo as the building tool, to solve the model with the aid of the GUROBI Optimization Solver.

4. CASE STUDIES AND RESULTS DISCUSSION

Averaging all mentioned case studies, the model consists of 4 396 743 constraints and 8 987 465 variables, making this model a high computational burden. As an average of all studies, the model took 5 872 seconds to build and 2 329 seconds to solve. It was executed on a computer with an AMD Ryzen 7 5800H processor and 16GB of RAM, using Windows 11 Home. The chosen modeling tool was Pyomo’s library [105], and it was solved using GUROBI’s Optimization Solver [106], coded using Python programming language. Memory utilization was measured using the *tracemalloc* library [107].

The methodology proposed in Chapter 3 is applied to a realistic 180-bus MV network in the Leiria district, Portugal.

4.1. CASE STUDIES’ DEFINITION

As previously mentioned, discount rate of 0.05% was used ([99], [100]), for a projected lifetime cycle of 30 years, leading to a CRF of 0.034. The study in [1] determined that the optimal cost to attribute to excessive generation would be 300 m.u./MWh (100, 200, 300, 400 and 500 m.u./MWh were analyzed). An implemented limit is imposed on the reliability indexes SAIDI and SAIFI to reduce them by at least 10% from their original values of 24.48 (h/customer) and 5.98 (int/customer), respectively.

The types of ESSs and lines follow the following in Table 19:

Table 19 - Options for ESSs and line types

Options for Energy Storage Systems					
Type	Capacity (MWh)	Power Rate (MWh)	Cost (m.u./kWh)	Cost (m.u.)	Maintenance Cost (m.u./year)
1	1	3.25	200	200 000	7 000
2	3	5.75	200	600 000	20 000

Options for Lines Connected to feeders		
Line	Upfront Buying Cost (m.u./km)	Maintenance Cost (m.u./km)
LXHIO1AV3x185mm^2	45 000	900
LXHIO1AV3x240mm^2	48 000	960
Option for all remaining Lines		
ACSR 160mm^2	32 000	1 600
ACSR 180mm^2	38 000	1 900

The cost for EENS is 3m.u./kWh, and the cost for power losses is 120m.u./MWh. Since this is the planning of an MV distribution network with a balanced three-phase system, all costs related to lines (implementation, maintenance, etc.) are multiplied by three.

The studied network's final characteristics are as follows in Table 20:

Table 20 – Nework's Final Characteristics

180 buses	**3 biomass generators**
90 loads	**42 Wind farms**
5 EV parking lots	**33 PV parks**
1 substation	**2 ESSs** **(The model may decide to install more)**

The PV modules and Wind turbines' characteristics remain unchanged from [1], while the biomass generators follow [103], [104], having a maximum capacity of 0.25MW each.

Along with the progress of this work, several studies were conducted at different points throughout the development, leading to all the publications mentioned in 1.5.

All the studies mentioned in the following list follow the network characteristics that were mentioned in this chapter, apart from the second study, related to uncertainty, where there were some slight differences in the network design (47 Wind farms instead of 42 and 37 PV parks instead of 33). This may lead to a slight discrepancy when comparing studies, but the difference is not impactful enough to disregard the case study.

As such, the case studies developed are as follows:

1) Base Network Study: where no investments are allowed, and the network is considered at face value, to create a common comparative baseline for all other case studies.

2) Hourly Uncertainty; Appliance of the multiplicative factors detailed in Table 16. through the method explained in 3.2. Moving from 16 original main situational scenarios to 8760 sub-scenarios. These scenarios are created through a Monte-Carlo method, where they suffer randomness through the normal distribution. Then the factors in Table 16 are applied to represent a broader spectrum of scenarios than initially. There is a base study with the Biomass generators included and an economic analysis with and without Biomass to understand its effects on the planning.

    1. General Study;
    2. Economic analysis considering Biomass generation;
    3. Economic analysis without considering Biomass generation.

3) Remuneration of Resources: Appliance of remuneration of resources, according to the values outlined in Table 17. The values are fixed and consider remuneration individually, to each producer. This is a considerable percentage of associated costs that were not previously considered. The uncertainty added in case 2 is still implemented.

    1. Study considering the need for remunerating all resources (DG and resources owned by the DSO);
    2. Study considering only what the DSO would need to pay to DG owners;

3. A brief study of different contracted approaches for the ESS, apart from the standard situation of 25% -- Studies for 25%, 50%, 75%, and 100%. (Details in Table 21.), and the possibility of adding capacity.

4) Risk-Aversion through VaR and CVaR: Consideration for the possibility of extreme events (in Fig. 17) occurring, even if the probability of occurrence is low. Six studies for different α (90%, 95%, and 99%) and β (0 and 1). Comparison between them regarding the Generation by Technology, Remuneration by Technology, and Total Associated Costs; Extra study to understand the relationship between CVaR and total cost (*tc*) for different values of β (increments of 0.1).

5) CO_2 Emissions: Implement adequate carbon emission for each generation unit, trying to minimize it along with the remaining network costs.

Table 21 - Different ESS possibilities

Housing Bus For the ESS	Percentage Owned by The DSO (%)	Percentage Owned by the Network Participant (%)	Current Installed Capacity (MW)	Maximum Possible Capacity (MW)
31	*25 / 50 / 75 /100**	*100 / 75 / 50 / 25*	1	5
87			3	5
Any Other Bus	100	--	--	3

*** Corresponding to the four different analyses made.**

This work was a gradual progression, meaning that the following cases are not meant to be compared to each other directly. It is also worth noting that the model portrayed in 3.2. is the final work, meaning that the model is not applied equally to all these cases studies, i.e., case study 2) or 3) do not consider equation (7), for example, since that refers to the risk aversion (CVaR), which had not yet been applied at that point. This is just an example to mention that, once again, this is a progression of work, and therefore, the model suffered changes along the way. While most of the model remained intact, the changes can be quickly summarized as follows:

- For case study 3), and all cases after, the remuneration of resources was added to equation (5) (PC_2, inside the box);
- For case study 3), and all cases after, constraints (25) and (26) were added;
- For case study 4), equation (7) was added – Equation (7) is not present in any other case studies;
- For case study 5), equation (6), was added – Equation (6) is not present in any other case studies.

The rest of the model is common to all case studies.

4.2. BASE NETWORK STUDY

This study is needed to allow for comparison with the new case studies, by giving them a common comparable benchmark for economic analysis. This case represents the analysis of the base network in Fig. 18, without allowing the model to perform any investments at all and relaxing all constraints. Table 22 shows all the outlined costs from this case. The SAIDI and SAIFI indicators were found to be 24.48 and 5.98, respectively.

This case does not yet consider the information added from 4.3. onwards (e.g., uncertainty, remuneration of RES, etc.).

Table 22 – Investment analysis for base network

Expenditures	Excessive Generation	17 272 000 m.u.
	Power Losses	3 098 000 m.u.
	EENS	5 552 900 m.u.
	Lines Maintenance	9 182 900 m.u.
Total		**35 105 800 m.u.**

All future economic analyses in this document will refer to the comparison with these values.

4.3. Hourly Uncertainty

As mentioned, this is the only case study where the network differs slightly, specifically in the changes to the number of DG units in the network and the two installed ESSs in buses 31 and 87.

4.3.1. General Study

In Fig. 19 the generation distribution in this specific case study can be seen, for illustrative purposes, from each source (Substation, Biomass, PV, and Wind) for each scenario. Each of the 16 shown values is a weighted average of all hourly scenarios for that situation, so the displayed results for Spring Morning (scenario 5) are a weighted average of all 460 hourly scenarios that belong to that main scenario (following the information in Table 15).

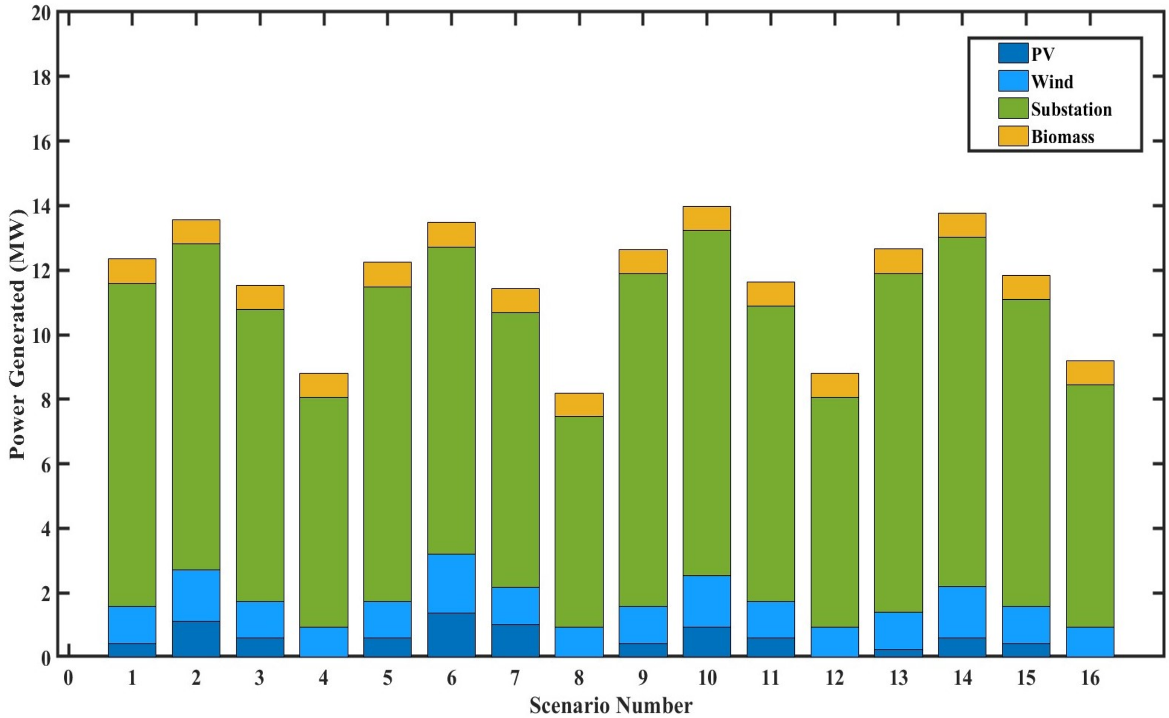

Figure 19 - Generation by technology for every scenario (Case Study 2)

The optimal network configuration for this case study is shown in Fig. 20. There are some unused lines, including connections 31-34, 106-128, 107-111, 138-169, 142-145, 156-158, and 164-166, as well as the selection of new lines to implement, including line 116-149 for feeder A and 1-102, 105-132, 143-146, 158-164, and 165-167 for feeder B. The model does not require access to energy from ESSs, as can be seen in Fig. 20, due to the high level of DG generation, thereby avoiding the associated implementation and maintenance expenses. Even though there is a small amount of excess generation from two generators (the Wind generators in buses 155 and 160), the quantity is insufficient to justify the addition of storage units, so the model opts not to use ESSs.

Significant improvements were made to the SAIDI and SAIFI, with final values of 20.43(h/customer), and 2.96 (int/customer), representing an improvement of 16.54% and 49.50%, respectively. This enhancement is primarily due to using a second feeder connection and respective transformer (1-102), so not all lines depend on the same one.

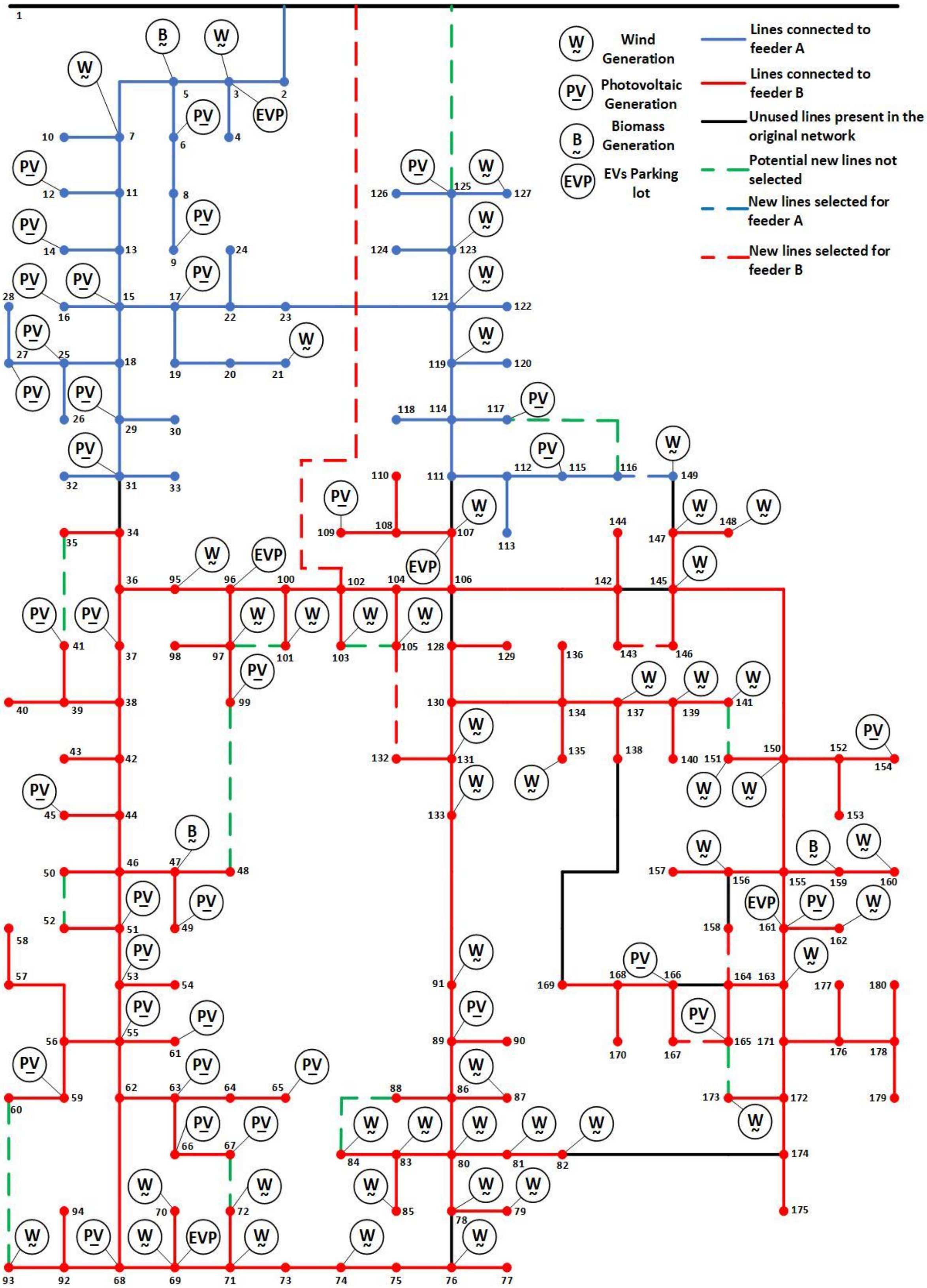

Figure 20 - Optimal network configuration for case study 2. All lines are color-coded according to their use or not, as well as which feeder they are connected to. (Original network adapted from [1]).

4.3.2. ECONOMIC ANALYSIS WITH BIOMASS

In Table 23, there is an analysis of costs regarding this case study considering Biomass generators, indicating the amount spent on expenditures and investments. Then, in Table 24, there is an economic analysis of NPV, IRR, and Payback.

Table 23 - Analysis of costs with biomass in Case Study 2

Investments	Lines	1 257 600 m.u.
	ESS	0 m.u.
	Total Investments	1 257 600 m.u.
Expenditures	Excessive Generation	26 887 m.u.
	Power Losses	547 875 m.u.
	EENS	1 262 646 m.u.
	Lines Maintenance	8 564 554 m.u.
	ESS Maintenance	0 m.u.
	Total Expenditures	10 401 962 m.u.
Total		**11 659 562 m.u.**

Table 24 - Economic analysis of case study 2 (with hourly uncertainty) and biomass

NPV	23 034 549 m.u.
Payback	1.54 years
IRR	64.92%

4.3.3. ECONOMIC ANALYSIS WITHOUT BIOMASS

Following the previous pattern, in Table 25, there is an analysis of costs regarding this case study without considering Biomass generators, indicating the amount spent on expenditures and investments. Then, in Table 26 there is an economic analysis of NPV, IRR and Payback.

Table 25 - Analysis of costs without biomass in Case Study 2

Investments	Lines	1 233 600 m.u.
	ESS	0 m.u.
	Total Investments	1 233 600 m.u.
Expenditures	Excessive Generation	0 m.u.
	Power Losses	2 460 363 m.u.
	EENS	6 060 546 m.u.
	Lines Maintenance	8 764 600 m.u.
	ESS Maintenance	0 m.u.
	Total Expenditures	17 285 510 m.u.
Total		**18 519 110 m.u.**

Table 26 - Economic analysis of case study 2 (with hourly uncertainty) and without biomass

NPV	16 178 422 m.u.
Payback	2.11 years
IRR	47.44%

4.3.4. COMPARISON WITH AND WITHOUT BIOMASS

It can be seen from the comparison of these Tables (23 to 26) that the use of these Biomass generators represents a big economic improvement which is because, had there not been Biomass generators, the generation deficit would need to be produced by the substation, which results in more power losses and EENS since most load points are then dependent on lines 1-2 and 1-102 not failing, which bumps up the cost as a result of possible failures (FOR). For comparison purposes and to better understand why the existence of these Biomass generators causes such a price drop, the amount of energy flow (for scenario 1), without Biomass generators, from bus 1 to 2 is 2.264 MW, and from 1 to 102 is 8.508 MW, while with Biomass generators from 1 to 2 is 1.657 MW and from 1 to 102 is 8.258 MW. This bump in the flow naturally results in higher costs regarding power losses and more load points are directly dependent on the connections to the feeders, which causes more costs if an outage occurs in those lines. There is also a slight network configuration change, as seen from the discrepancy in the lines' investments presented in Table 23 and Table 25. However, when analyzing the total cost, it is very minimal. Additionally, not using the biomass generators represents a 6.2% improvement in SAIDI and a 28% improvement in SAIFI.

4.4. REMUNERATION OF RESOURCES

In this case study, two different approaches were taken. One approach involved considering the remuneration of all resources, while the other approach focused specifically on compensating the Distributed Generators (DG) present in the network.

A study where only third-party generation (PV, Wind, and ESSs) is remunerated is needed to look at the problem from the DSO's perspective, though the first study is done either way if the DSO must pay for the substation and biomass generators to an external supplier.

There is also a very brief study done to understand the effects of changing the percentage of accessible ESS capacity through the contracts mentioned above on buses 31 and 87.

All these studies, and all studies moving forward, also consider the hourly uncertainty mentioned before in 4.3. This study would be a combination of adding uncertainty to PV/Wind generation and Load and adding the remuneration of resources.

4.4.1. STUDY FOR REMUNERATION OF DG UNITS ONLY (NO DSO-OWNED GENERATION CONSIDERED WHEN MINIMIZING)

Even though the model is now considering a new part of the objective function (see remuneration on equation (5)), and the two ESSs have been added, the final network topology remains unchanged from case study 2, as can be seen in Fig. 23, apart from line 117-116, instead of 115-116. Even though this occurs, there are changes to the total expenditure and investments, as expected, since there is now consideration for a previously disregarded cost. While in this case study, there is still a calculation of the price of DSO-sided generation, it is merely for comparative purposes since it was not considered when minimizing the costs (only want to consider what the DSO needs to pay to outside parties).

In Fig. 21 there is the total generation by technology in this case study. Again, the generation for each scenario is a weighted average of all hourly scenarios within the main scenario, as explained in 4.3.

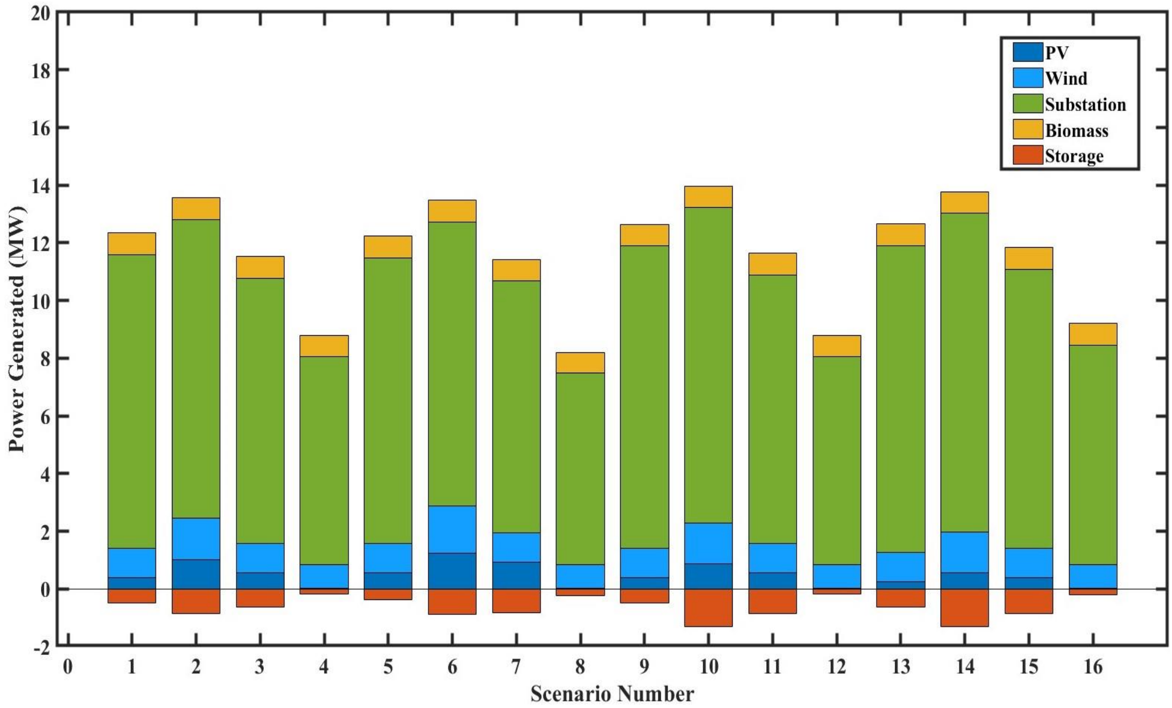

Figure 21 - Generation by technology for each main scenario (Case Study 3.A.)

As seen, a large portion of generation is upheld by the substation still since it is an extensive network. The three Biomass generators are also used near their maximum capacity since the DSO owns them and can manage them as needed. The variation within scenarios depends on the surrounding circumstances, i.e., negligible PV generation at night requires a different generation pattern, even if there is much less demand to be met. Primarily, the ESS in bus 31 is being used to feed the network (apart from scenarios 12 and 16, which are Fall and Winter at Night). In contrast, the ESS in bus 87 is being charged in all scenarios, where the third-party owner is assumed to pay the DSO for the corresponding quantity, as seen in Fig. 22. In Fig 21. the ESSs are noticeably less prominent during the night scenarios since there is much less demand and PV generation as well. Remuneration follows equation (38) (example for substation, same method for other generation technologies).

$$SubRem = \sum_{s \in \Omega_S} \left(P_{Sub(bs,s)} \cdot hoursPer_{(s)} \cdot Sub_{\mathrm{Pr}ice} \right) \cdot CRF \tag{38}$$

Where *PSub* is the generation of the substation on a specific scenario, *s*; *hoursPer* is the amount of hours in that scenario, *s*; *SubPrice* is the price to remunerate to that technology (substation in this case), following the values in Table 17; and *CRF* is the capital recovery factor, as explained in section 3.7. While it may seem unnatural for nightly scenarios to be the most expensive, it is due to them being assigned the most hours, as specified before in Table 15.

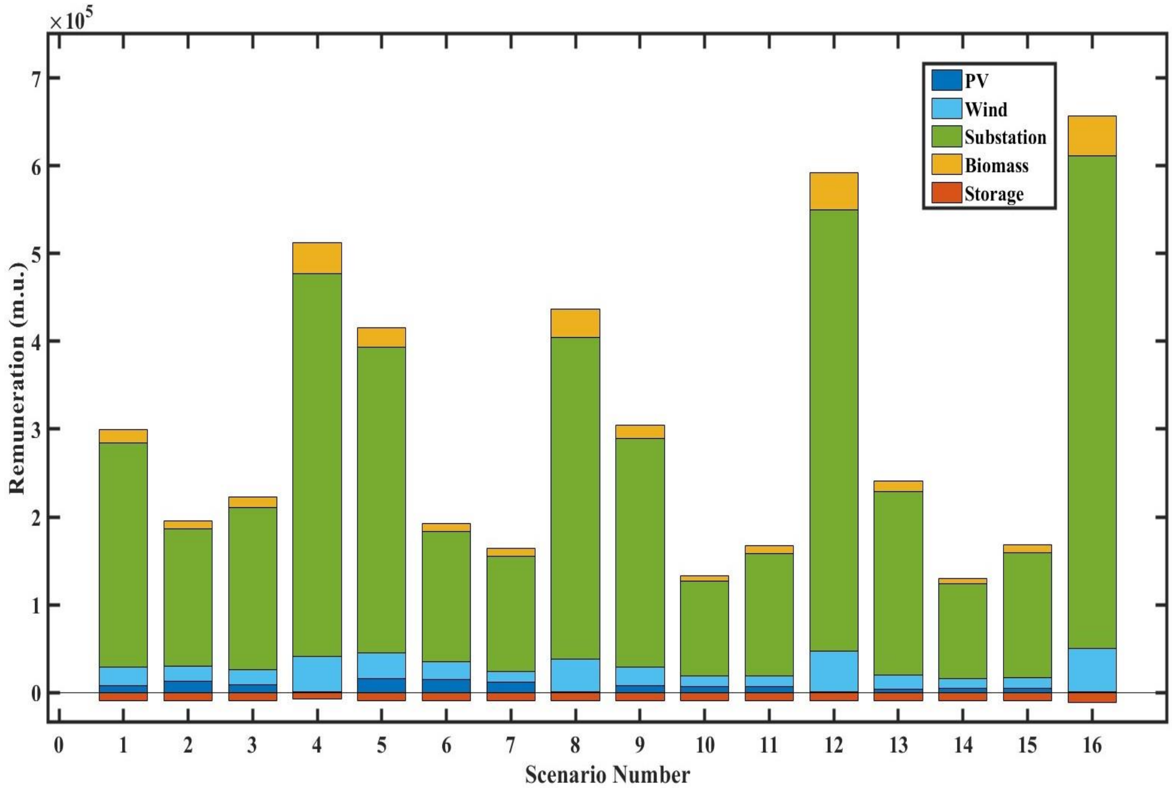

Figure 22 - Remuneration for each technology in each main scenario (Case study 3.1)

Since the primary purpose of this model is to reduce the total costs for the DSO, a detailed analysis of the total expenses is made in Table 27.

An economic evaluation was also made to understand how valuable the model is, by evaluating the economic indicators NPV, Payback, and IRR, as previously mentioned, and it is shown in Table 28.

Table 27 - Analysis of costs in case study 3.1.

Investments	Lines (Including Transformer Cost)	1 257 600 m.u.
	ESS	400 000 m.u.
	Total Investments	1 657 600 m.u.
Expenditures	Excessive Generation	26 887 m.u.
	Power Losses	556 580 m.u.
	EENS	1 280 487 m.u.
	Lines Maintenance	8 564 554 m.u.
	ESS Maintenance	1 203 755 m.u.
	Total Expenditures	11 632 263 m.u.
Total Network Planning Costs		**13 289 863** m.u.
Remuneration (Yearly)	Substation	5 258 321 m.u.
	Biomass	389 621 m.u.
	Wind	585 655 m.u.
	PV	390 621 m.u.
	Storages	-157 169 m.u.
Total Remuneration Associated Costs		**6 467 049** m.u.
Total Costs		**19 756 912** m.u.

Table 28 - Economic analysis of case study 3.1.

NPV	14 699 358 m.u.
Payback	3.02 years
IRR	33.16%

While considering a whole new cost type (remuneration of resources), the model is still very appealing economically. Naturally, it would seem beneficial to disregard this consideration at first glance. Still, it must be considered since it cannot be avoided realistically. It is also seen that the ESSs represent a gain and not an investment in this specific study since it is assumed that the ESS owner pays the DSO for charging the ESS (currently, the same pay rate is assumed while charging and discharging, but this may suffer alterations in future work variations). In this case study, the ESS on bus 31 was type 1, and the one on bus 87 was type 2 (Table 21).

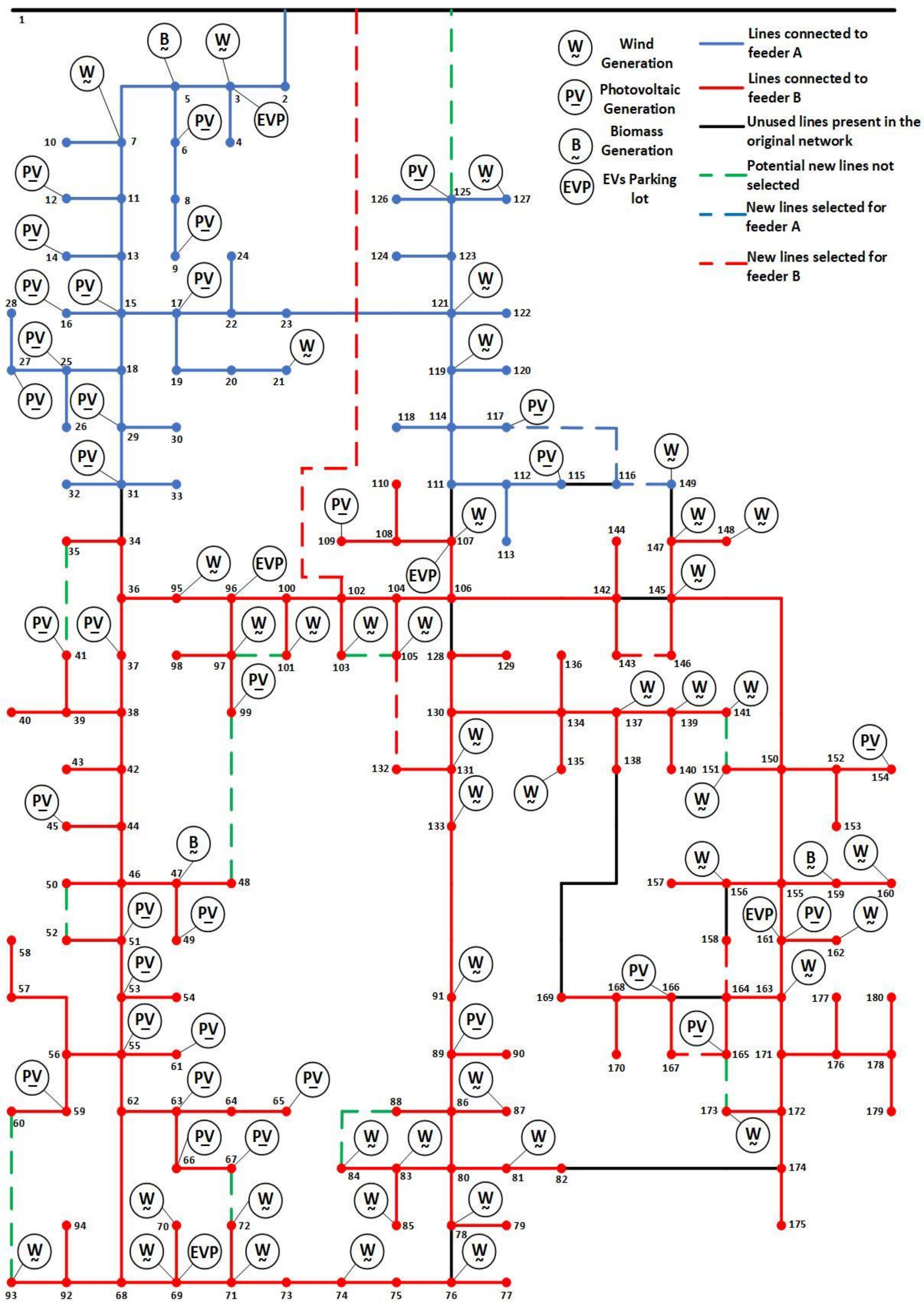

Figure 23 - Optimal network configuration for case study 3. All lines are color-coded according to their use or not, as well as which feeder they are connected to. (Original network adapted from [1]).

Here, the reliability indicators SAIDI and SAIFI end up at 19,23h/customer and 2,94 int/customer, representing a 21.44% and 49.84% improvement (compared to the original network), respectively.

4.4.2. STUDY FOR ALL GENERATION SOURCES (INCLUDING THE ONES OWNED BY THE DSO)

In this study, there is an aim to minimize the remuneration of all resources as if nothing was owned by the DSO (e.g., the substation and biomass were owned by an external supplier) for a hypothetical situation.

While there is no change regarding the network topology (remains the same as Fig. 23), some interesting effects happen regarding the generation pattern (Fig. 24), namely the fact that there is a decrease in substation generation and the ESSs are now exclusively used to feed the network's demand. This makes sense since, if all technologies' remuneration is considered to be minimized, the substation suffers a decrease since it is the most expensive (Table 17).

In this case, the reliability indicators SAIDI and SAIFI see an even bigger improvement when compared to 4.4.1., with the SAIDI ending up at 19.20h/customer, a 21.54% improvement from the original network (4.2.) and the SAIFI ending up at 2.93, a 51.00% improvement. This is mainly due to a slightly reduced reliance on the lines connecting to the feeder since the amount of generation from the substation slightly decreases, and, as such, the power flow is more divided among other lines, namely through a positive use of the ESSs in place. As previously mentioned, this can be observed in Fig. 24, while the remuneration by technology is depicted in Fig. 25.

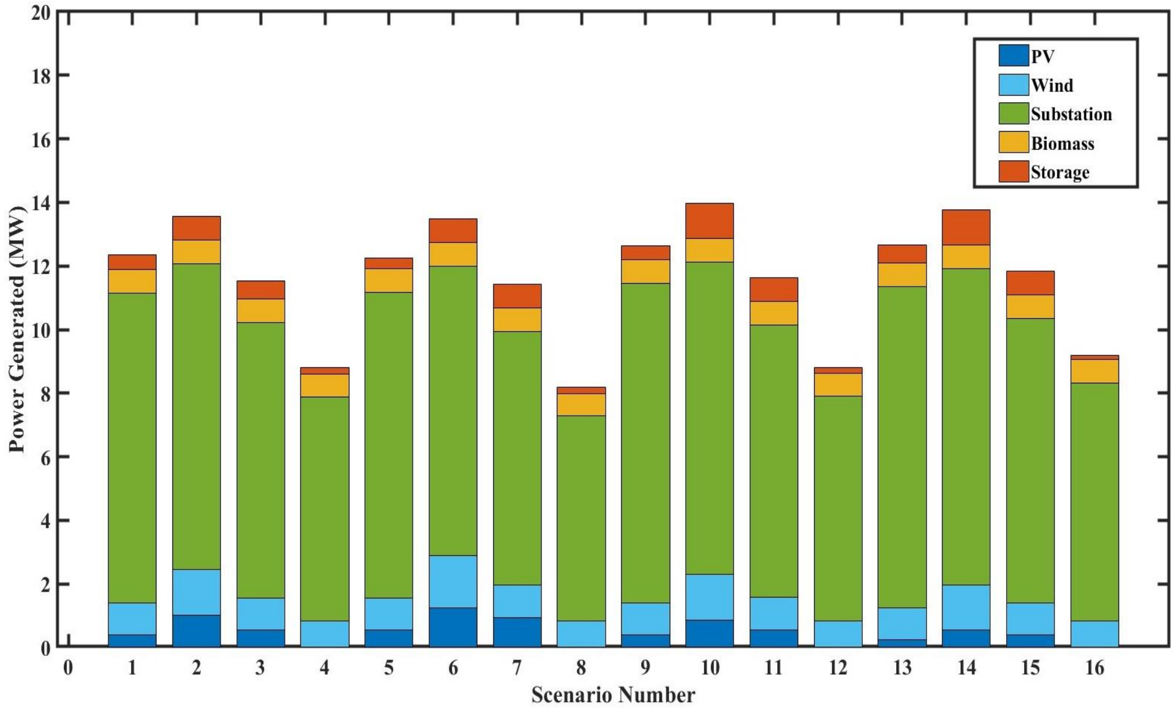

Figure 24 - Generation by technology for each main scenario (Case study 3.2.)

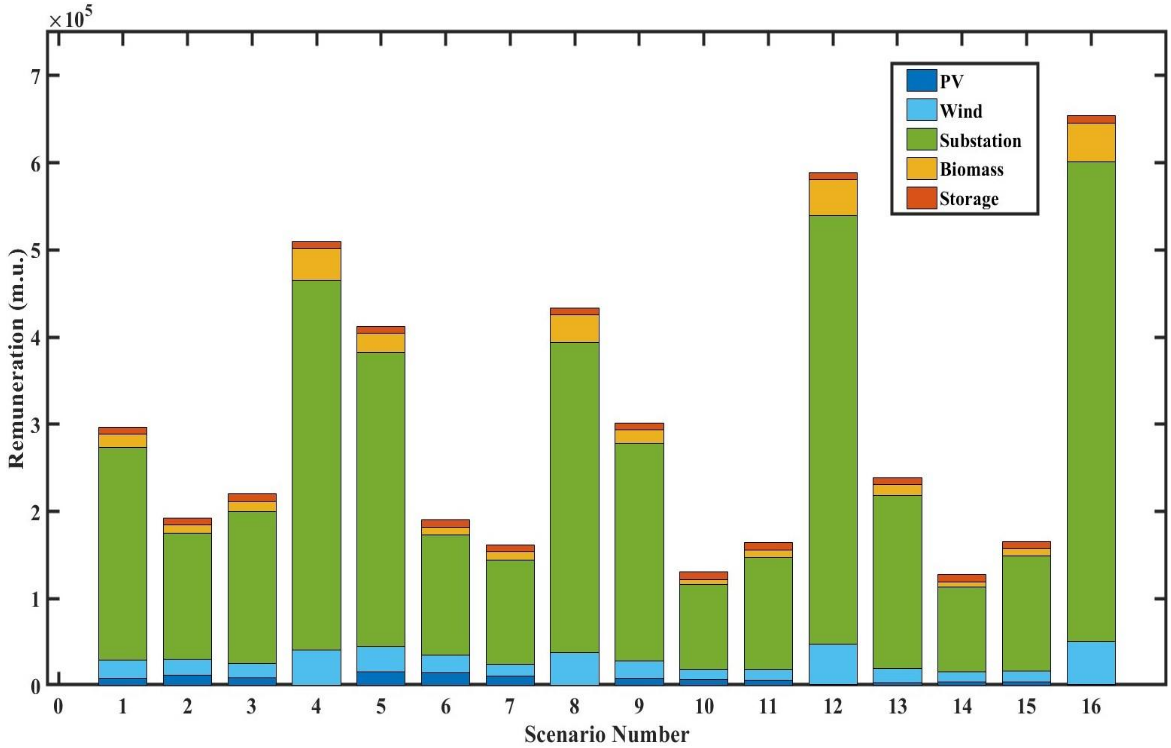

Figure 25 - Remuneration for each technology in each main scenario (Case study 3.2.)

Regarding the costs for the DSO, the investments and expenditures remain the same, with only the remuneration side of costs and the economic analysis changing. Table 29 shows the costs for this case (Remuneration only since the rest remains the same), and Table 30 shows the economic analysis.

Table 29 - Analysis of costs in case study 3.2.

Total Network Planning Costs		**13 289 863 m.u.**
Remuneration (Yearly)	Substation	4 961 252 m.u.
	Biomass	359 621 m.u.
	Wind	585 655 m.u.
	PV	390 621 m.u.
	Storages	118 777 m.u.
Total Remuneration Associated Costs		**6 415 926 m.u.**
Total Costs		**19 705 789 m.u.**

There is a very slight decrease in total costs here since all associated parts are being minimized, also resulting in a slightly better economic analysis.

Table 30 - Economic analysis of case study 3.2.

NPV	14 750 455 m.u.
Payback	3.01 years
IRR	33.26%

While the solution is preferable economically, the model chooses to ignore the contracted limit in some scenarios, seemingly preferring it to sustain the costs of transporting the electricity that would otherwise need to be generated by the substation. Table 31 outlines all contract states for both ESSs (buses 31 and 87), showing the excess amounts in the situations where they do happen.

Table 31 – States of ESSs (Out of contract excess)

Main Scenario	Excess Bus 31 (MW)	Excess Bus 87 (MW)	***Main Scenario***	Excess Bus 31 (MW)	Excess Bus 87 (MW)
1	None	None	***9***	None	None
2	None	None	***10***	None	0.031
3	0.020	0.190	***11***	0.006	0.076
4	0.028	0.097	***12***	0.012	0.088
5	None	None	***13***	None	0.007
6	None	None	***14***	0.028	0.008
7	0.020	0.090	***15***	0.006	0.076
8	0.020	0.091	***16***	0.020	None

It is worthily to note that the DSO pays the out-of-contract price only for the excess amount past the contracted 25%.

4.4.3. DIFFERENT ESS CONTRACTUAL CAPACITIES

This study did not result in any conclusive changes. This source's consumption would remain unchanged for all available ESS percentages. For the situations where there would be access to the ESS past the contracted value (Table 31), now there was no excess, which resulted in a very slight decrease in total cost. However, assuming that the contract would also be more expensive to begin with, this is not very important, and, as such, 25% is the optimal quantity for the contract in this network, among the considered percentages of 25%, 50%, 75%, and 100%.

While this happens in these specific ESSs, there is no guarantee that this would still be the case if the ESSs were allocated to any other buses in the network. For instance, in [108], Bhattarai et al. find that the preferable percentage of allowed storage capacities varies considerably according to its allocation in the network.

4.5. Risk-Aversion through CVaR

In this study, there is an aim to prepare the network for extreme events.

This study also has some slight changes to the order of the scenarios. The scenarios depicted in Table 15 are changed to the following in Table 32:

Table 32 - New scenario order only for case studies 4 and 5

Season	Season Days	Hours/Season (h)				Scenario Probability			
		Night	Morning	Peak	Afternoon	Night	Morning	Peak	Afternoon
Spring	92	1104	460	276	368	12.60% *(1)*	5.25% *(2)*	3.15% *(3)*	4.20% *(4)*
Summer	92	1012	644	276	276	11.55% *(5)*	7.35% *(6)*	3.15% *(7)*	3.15% *(8)*
Fall	91	1274	455	182	273	14.54% *(9)*	5.19% *(10)*	2.08% *(11)*	3.12% *(12)*
Winter	90	1350	360	180	270	15.41% *(13)*	4.11% *(14)*	2.05% *(15)*	3.08% *(16)*

For the numerical analysis of Generation by Technology, Remuneration by Technology, and Total Associated Costs, there is a detailed analysis for the study of α=90%/95%/99% and β=0 (all three have the same results since there is no risk aversion in these cases). The other studies (α=90%/β=1, α=95%/β=1, α=99%/β=1) are compared through a percentage difference. There are 64 sub-scenarios here, four for each main scenario. For example, main scenario 2, Spring Morning, has sub-scenarios 5-8.

In Fig. 26 is the final network depicted for this case study.

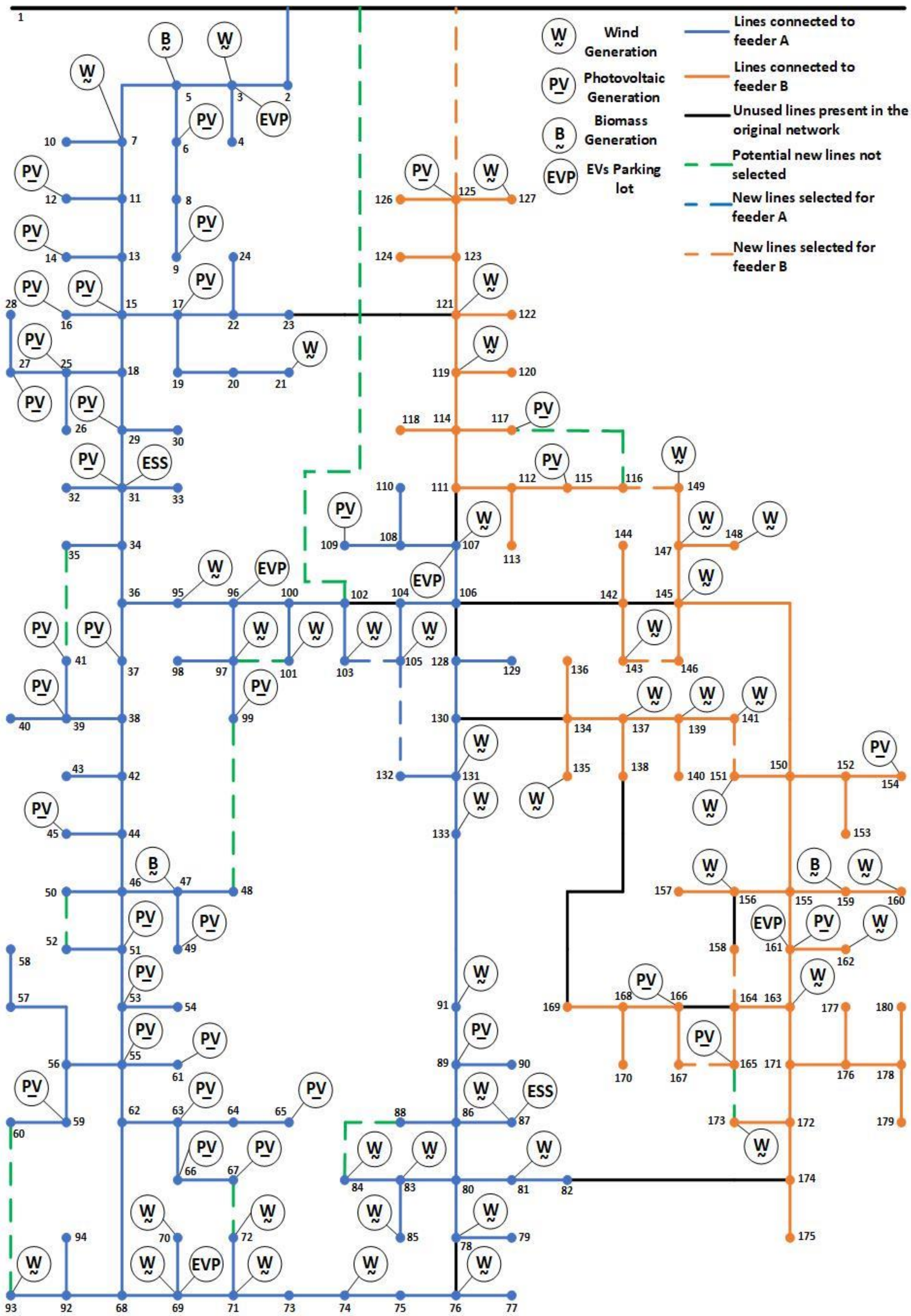

Figure 26 - Optimal network configuration for case study 4 (α=90%/95%/99% and β=0). Original network adapted from [1]).

The model proposes installing some new power lines, e.g., 105-132. Additionally, there is a new feeder installation with a new transformer in 1-125. The tests for α=95%/β=1 and α=99%/β=1 do not present any changes to the topology, and the test for α=90%/β=1 swaps the line 78-80 with the line 76-78, and the line 165-167 with 164-166. All these changes result in final values of 20.38 h/customer and 4.09 int/customer for SAIDI and SAIFI, respectively. This represents an improvement of 20.12% and 46.21% in the mentioned indexes. The α=90%/β=1 case has values of 20.33 h/customer and 4.06 int/customer (20.41% and 47.29% improvement). The model also proposes to add an additional ESS on bus 66 on the simulation α=90%/β=1 and two ESSs on buses 66 and 137 for α=95%/β=1 and α=99%/β=1.

Fig. 27. shows the generation pattern for the risk-neutral approach, i.e., β=0 for the entire 64 sub-scenarios. Some interesting points in this chart are a consequence of what was considered according to Fig. 17. There is a major increase in substation power supply in sub-scenario 3 compared to the other three sub-scenarios in the same main scenario (1, 2, and 4) to help meet the load increase. Sub-scenarios 14 and 45 have the most significant generation pattern changes. In sub-scenario 14, the combination of no ESSs and biomasses, along with the load demand and EVP charge increase, resulted in a significant dependence on substation power, which resulted in a considerable increase in EENS and power loss costs for that sub-scenario.

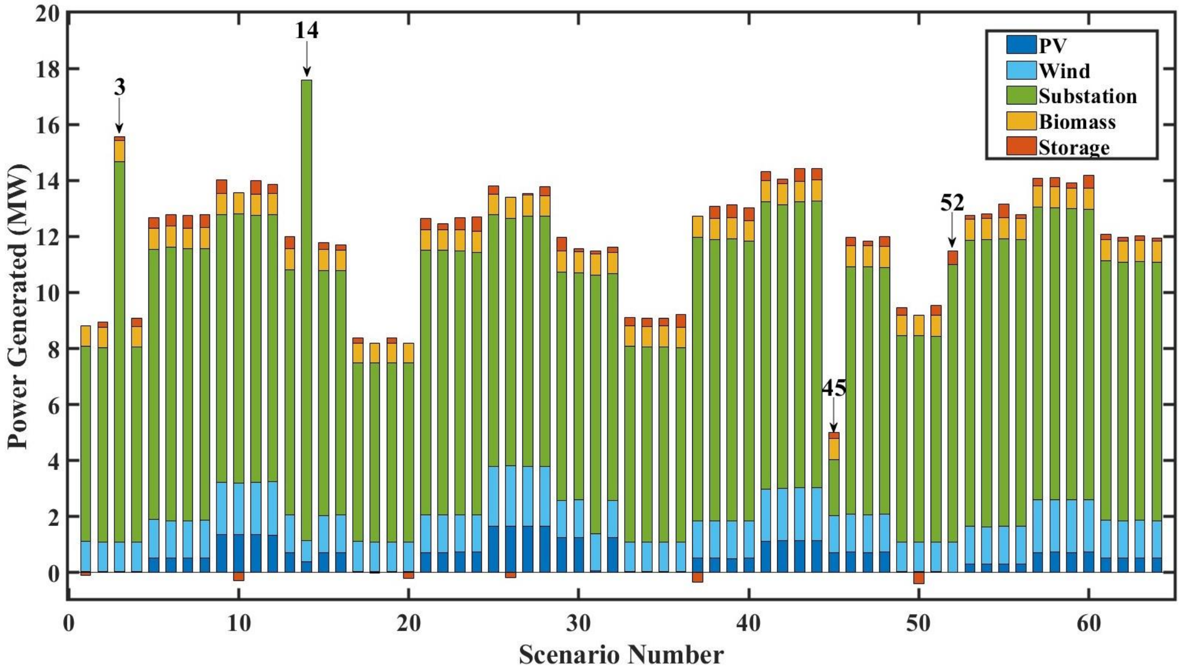

Figure 27 - Generation for the 64 sub-scenarios in case study 4 (α=90%/95%/99% and β=0)

Fig. 28 shows the associated remuneration cost for all 64 sub-scenarios. In sub-scenario 45, the smallest generation for any sub-scenario occurs, given that the substation was limited to 2MW. While this may seem appealing regarding the cost associated with the remuneration of resources (as seen in Fig. 28.), that results in a major cost increase to the load cut-related costs. Sub-scenario 45 is the most expensive, as seen in Fig. 30. In sub-scenario 52, not allowing the biomass generators leads to a significant increase in total generation (due to the substation supply increase) when compared to sub-scenarios 49, 50, and 51 (same main scenario, 13).

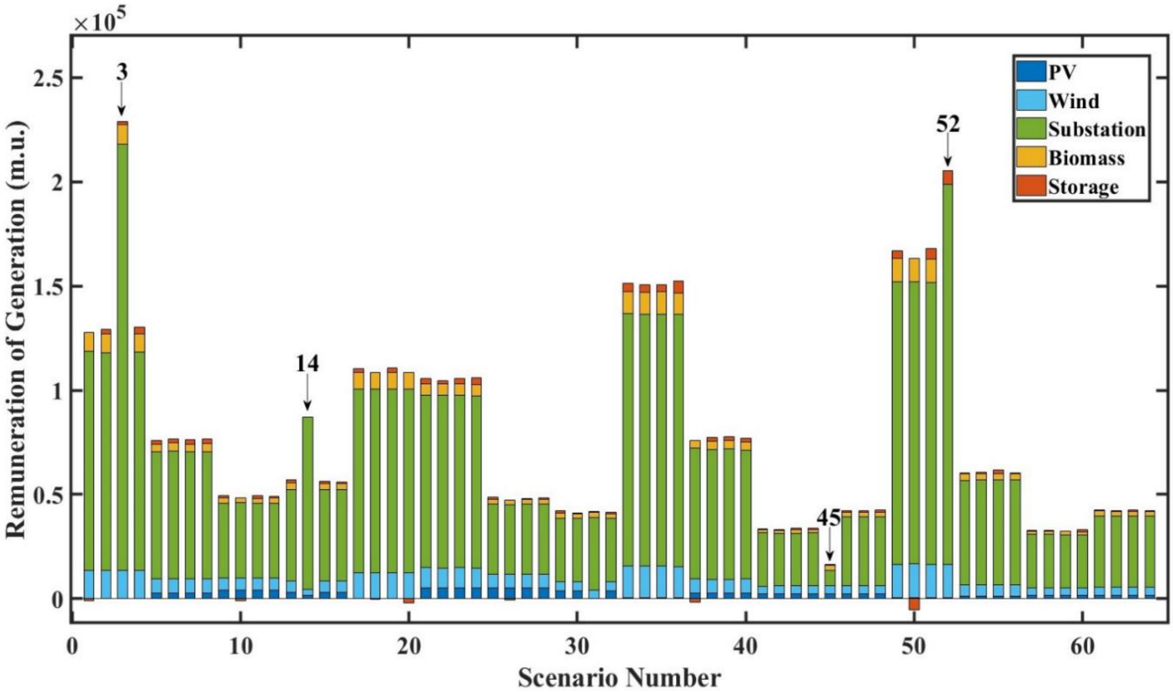

Figure 28 - Remuneration of resources for the 64 sub-scenarios in case study 4 (α=90%/95%/99% and β=0)

When analyzing both Figs. 27 and 28, there is a discrepancy between the amount of generation and remuneration. This is due to the remuneration also being dependent on other factors, such as the scenario probability calculated through equation (2), which varies depending on the main scenario probability. For instance, in Fig. 27, sub-scenario 14 requires more generation than sub-scenario 3, but in Fig. 28, it is seen that sub-scenario 3 more than doubles the needed remuneration of resources when compared to sub-scenario 14, which is mainly because main scenario 1 (sub-scenarios 1-4) has a 12.60% combined probability and main scenario 4 (sub-scenarios 13-16) only has a combined 4.20% probability (see Table 32). In Table 33, there is a percentage comparison between the case (α=90%/95%/99% and

β=0) in Fig. 27 and the other studies (α=90%/95% /99% and β=0) regarding generation and remuneration.

Table 33 - Percentage comparison of generation and remuneration - Case study 4

Case Study	Generation (MW)	Remuneration of DG (m.u.)
α=90/95/99% β=0	767.08	5 019 329
α=95% β=1	800.06 (+4.3%)	5 139 739 (+2.4%)
α=99% β=1	817.70 (+6.6%)	5 205 045 (+3.7%)
α=90% β=1	775.51 (+1.1%)	5 054 465 (+0.7%)

Table 33 shows the results that were expected because when considering risk-aversion, the model focuses mainly on the most expensive sub-scenarios (top 2 for α=99%, top 4 for α=95%, and top 7 for α=90%), leading to the remaining sub-scenarios suffering a slight increase in most cases. There were no breaches of ESS contracts in any sub-scenario in any case. Fig. 29 presents a graphical analysis of the changes to the VaR and CVaR of all the case studies. While considering risk-aversion with α=90%, the CVaR had a reduction of 17.9%, with α=95%, it was 25.4% reduction, and with α=99%, it was 39.9%.

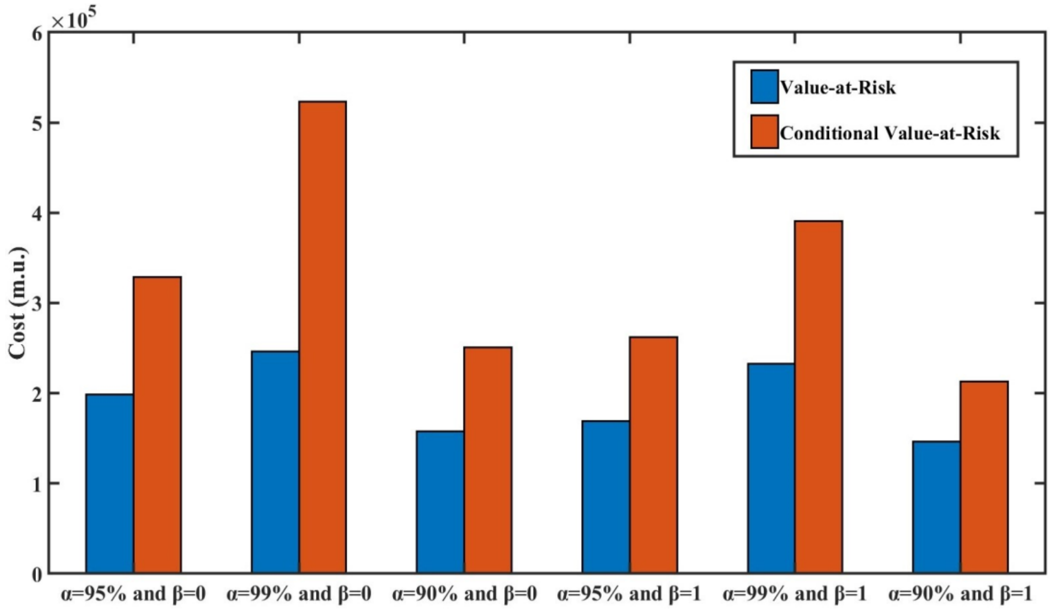

Figure 29 - VaR and CVaR for all studies in case study 4

All risk-aversion studies suffer decreases from their risk-neutral counterparts (with the same confidence level) in VaR and CVaR, as expected. The total outline of all sub-scenario costs is seen in Fig. 30 where there are interesting patterns according to the extreme scenarios implemented in Fig. 17.

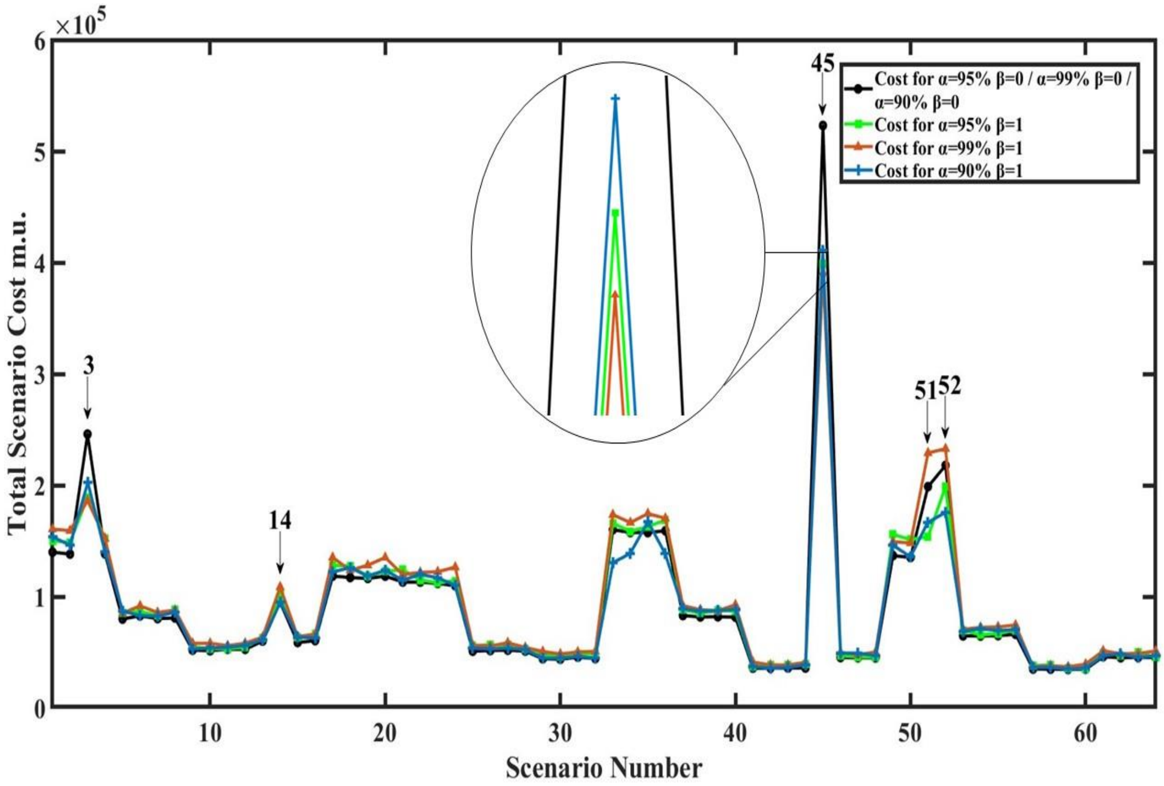

Figure 30 - Total scenario cost for all 64 sub-scenarios

The most problematic sub-scenario is sub-scenario 45, where the limitation of substation capacity to only 10% leads to a substantial load cut cost, which was reduced by 31% when considering risk aversion with a confidence level of 95%, reduced by 34% when considering a confidence level of 99%, and 27% with a 90% confidence level. Most sub-scenarios suffer a cost increase when considering risk aversion (as expected). Sub-scenarios 51 and 52, for example, only suffer an increase in cost for the 99% confidence level since they are not included in the alpha percentile above *αPercPos* in the 90% and 95% cases. Sub-scenario 14 does not represent a significant portion of the costs, despite being extreme regarding the generation pattern, for the abovementioned reasons regarding the scenario probability. Table 34 presents the detailed costs for the risk-neutral approach.

Table 34 - Total costs for α=90/95/99% and β=0; Case study 4

Investments	Lines (Including Transformer Cost)	1 253 550 m.u.
	ESS	400 000 m.u.
	Total Investments	**1 653 550 m.u.**
Expenditures	Excessive Generation	5 554 m.u.
	Power Losses	375 372 m.u.
	EENS	1 244 552 m.u.
	Lines Maintenance	8 433 230 m.u.
	Load Cut	521 420 m.u.
	ESS Maintenance	864 392 m.u.
	Total Expenditures	11 444 520 m.u.
Total Network Planning Costs		**13 098 070 m.u.**
Remuneration (Yearly)	Substation	4 033 655 m.u.
	Biomass	275 373 m.u.
	Wind	489 626 m.u.
	PV	142 186 m.u.
	Storages	78 489 m.u.
Total Remuneration Associated Costs		**5 019 329 m.u.**
Total Costs		**18 117 399 m.u.**

Most of the total cost derives from the maintenance of lines and the remuneration of resources. The entirety of the load cut costs are a result of sub-scenario 45. All the displayed costs result in the economic analysis represented in Table 35, where the total costs of all scenarios are also compared.

Table 35 – Total costs and economic analysis comparison – Case study 4

Case	**Total cost (m.u.)**	**NPV (m.u.)**	**Payback (years)**	**IRR (%)**
α=90/95/99% β=0	18 117 399	9 884 389	4.26	23.41
α=95% β=1	18 939 550 (+4.5%)	9 084 788	4.58	21.77
α=99% β=1	19 402 652 (+7.2%)	8 585 037	4.81	20.74
α=90% β=1	18 631 572 (+2,8%)	9 384 639	4.46	22.38

The total cost increases with a higher confidence level. Even though the effects of the most extreme scenarios are not too significant in the *α=90% / β=1* case, the total cost is still less than in the other cases. This is due to the load cut and resource remuneration costs being considerably reduced for the top 10% percentile sub-scenarios. The model is economically interesting, as seen by the results compared to the original network, which had a total cost shown in chapter 4.2., 35 105 800 m.u.

With an increase of 7.2% of the total costs (the biggest among the studied cases), the case of *α=99% / β=1* also represents the biggest reduction in the cost of the most extreme sub-scenario (34%), which represents the tradeoff between preventing possible extreme events and not considering them in the expansion planning model. Even if there is a slightly worse overall economic interest in normal circumstances, if the extreme sub-scenario happened to occur, the network would be prepared to contradict the effects.

Regarding the study that was conducted to understand the relationship between *tc* (total cost) and *CVaR*, increments of 0.1 were used in *β*, resulting in 10 different comparisons. Fig. 31 presents the obtained pattern for all values of *β* for $CVaR/t_c$. The charts show the pattern for a confidence level, *α*, of 99% (red), 95% (green), and 90% (blue).

The pattern is coherent across the three confidence levels, *α*. The increase in the risk-aversion, *β*, results in a lower *CVaR* and a higher t_c. For the study where *α*=90%, an ESS (bus 66) was installed for all values of *β*, and two ESSs (buses 66 and 137) were installed on *α*=95/99%. There are some interesting behaviors in the model on certain occasions. For instance, with *α*=95%, an abrupt drop in CVaR occurs from *β*=0.9 to *β*=1. This matched with a network topology shift, i.e., changing in some lines, resulting in a slight increase in line implementation costs but a considerable decrease in EENS and power loss costs and the load curtailment that occurred in sub-scenario 45. The pattern of VaR/t_c is similar to the one displayed in Fig. 31.

The cost type that seems to be most affected in non-extreme sub-scenarios is the EENS and power loss costs. The risk-aversion in the model mainly affects the load cut and remuneration costs in the extreme scenarios.

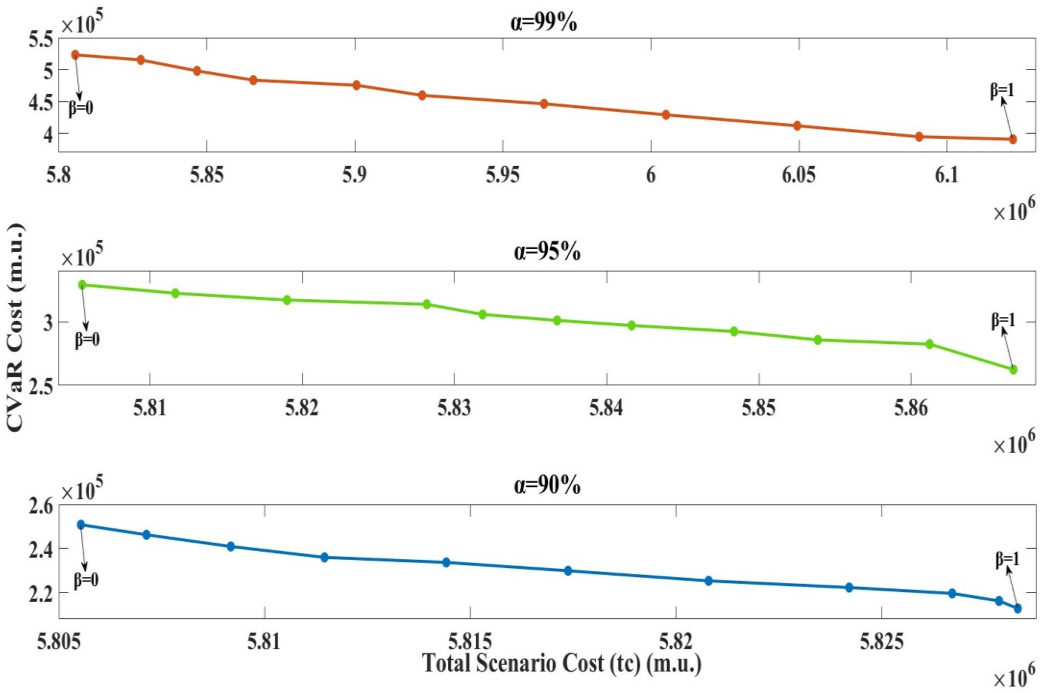

Figure 31 - Evolution pattern of CVaR/tc for 0.1 increments of β - Case study 4

4.6. CO_2 EMISSIONS

Regarding the study where the minimization of CO_2 emissions was implemented, the final network configuration is as represented in Fig. 32. For this case study, equation (6) was implemented into the objective function using the considerations explained in chapter 3.5.

The model proposes installing several new lines, e.g., 103-105, a new feeder installation, and a new transformer in 1-125. The final values of SAIDI and SAIFI are 20.39h/customer and 4.10 int/customer, corresponding to a 20.11% decrease for the SAIDI and 47.25% for the SAIFI. The total listing of costs is shown in Table 36.

The economic analysis regarding the model can be seen in Table 37.

In Figs. 33 and 34 are the Generation by Technology and Remuneration by Technology for this case study.

Furthermore, in Fig. 35, the total carbon emissions are exposed in tons. The results in Fig. 35 are to be expected since the majority of the network's generation is still provided by the substation, which is also assumed to have slightly higher emission rates (Table 18).

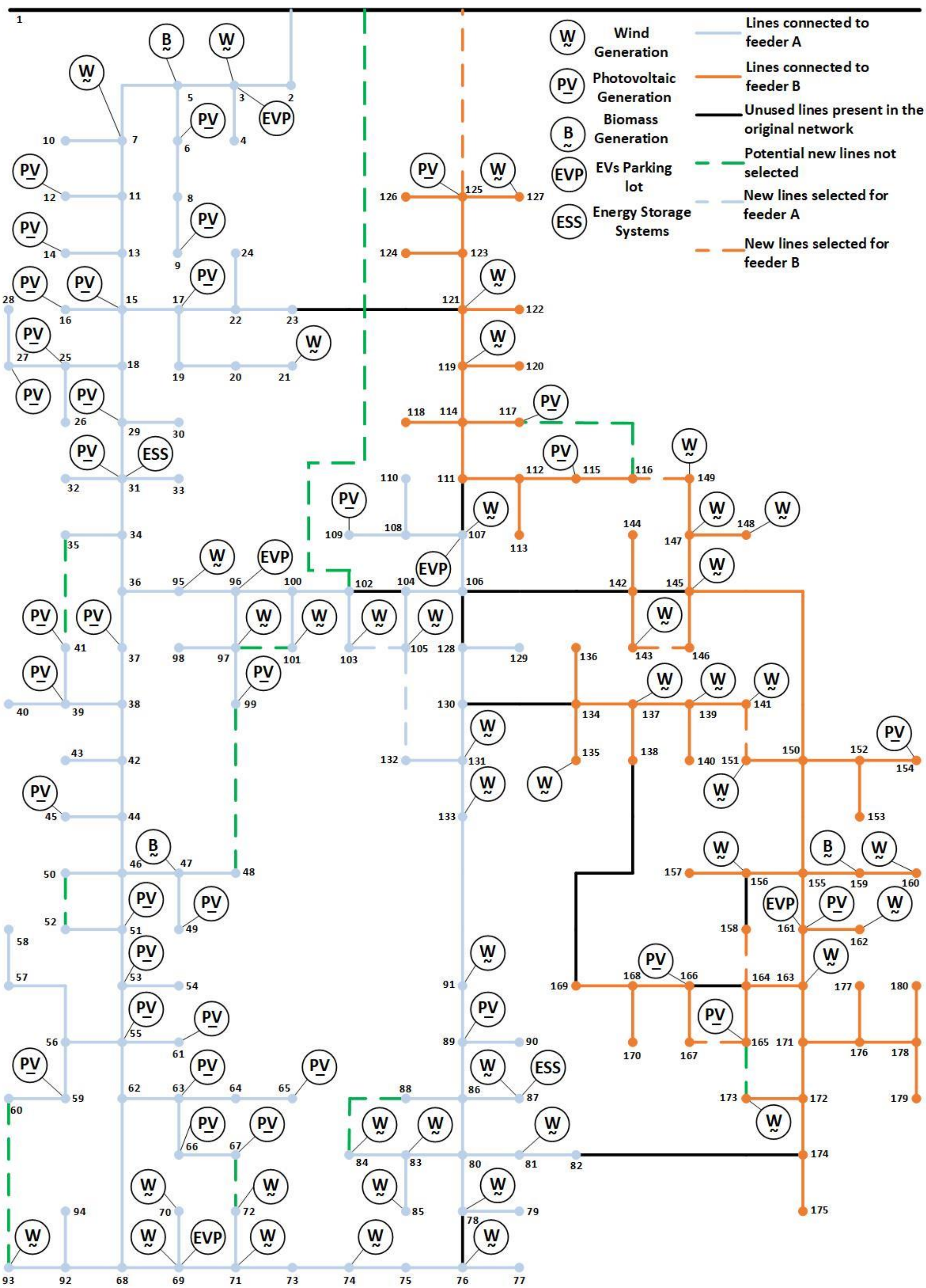

Figure 32 - Optimal network configuration for case study 5. (Original network adapted from [1]).

Table 36 - Total listing of costs for case study 5

Investments	Lines (Including Transformer Cost)	1 253 550 m.u.
	ESS	400 000 m.u.
Expenditures	Excessive Generation	5 654 m.u.
	Power Losses	220 688 m.u.
	EENS	1 235 604 m.u.
	Lines Maintenance	8 433 230 m.u.
	ESS Maintenance	864 392 m.u.
Remuneration (Yearly)	Substation	3 900 161 m.u.
	Biomass	291 880 m.u.
	Wind	499 340 m.u.
	PV	144 910 m.u.
	Storages	16 252 m.u.
CO_2 Emissions	Substation	2 169 908 m.u./42 547 tons
	Biomass	248 099 m.u./4 865 tons
	Wind	15 619 m.u./306 tons
	PV	9 591 m.u./188 tons
	Storages	201 m.u./4 tons
Total Costs		**19 691 032 m.u.**

Table 37 - Economic analysis for case study 5

NPV	8 356 240 m.u.
Payback	4.92 years
IRR	20.26%

Despite including resource remuneration and CO2 emission costs, the proposed model demonstrates a compelling economic appeal, characterized by a relatively abbreviated payback period (4.92 years).

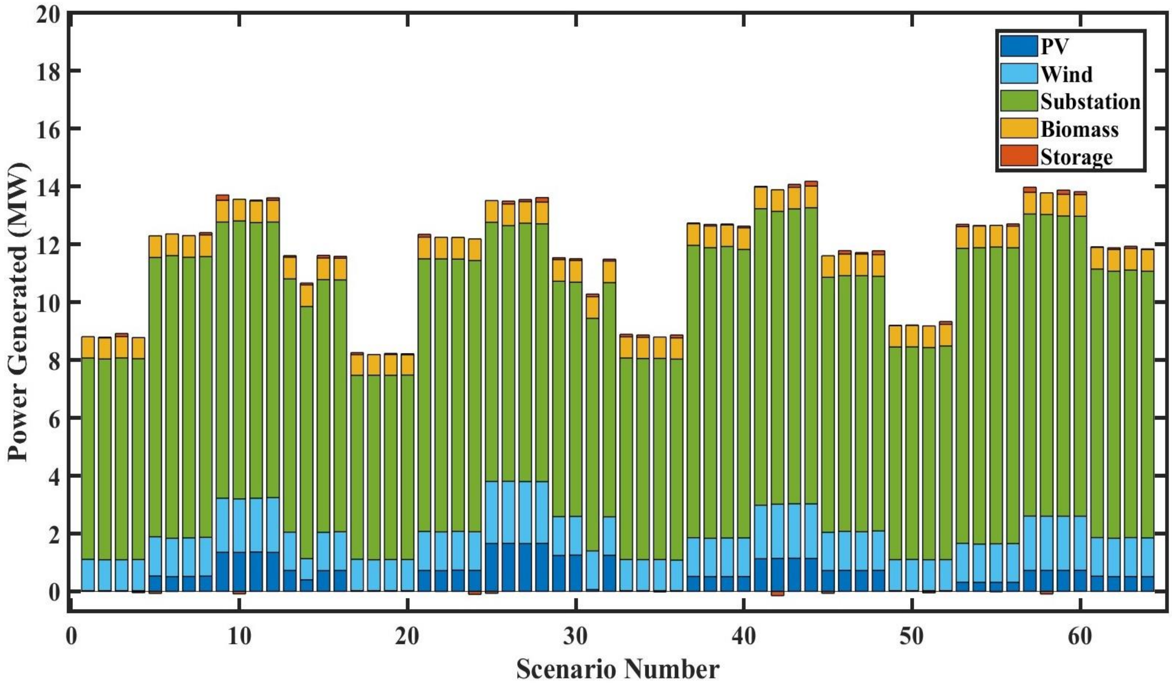

Figure 33 - Generation for the 64 sub-scenarios in case study 5

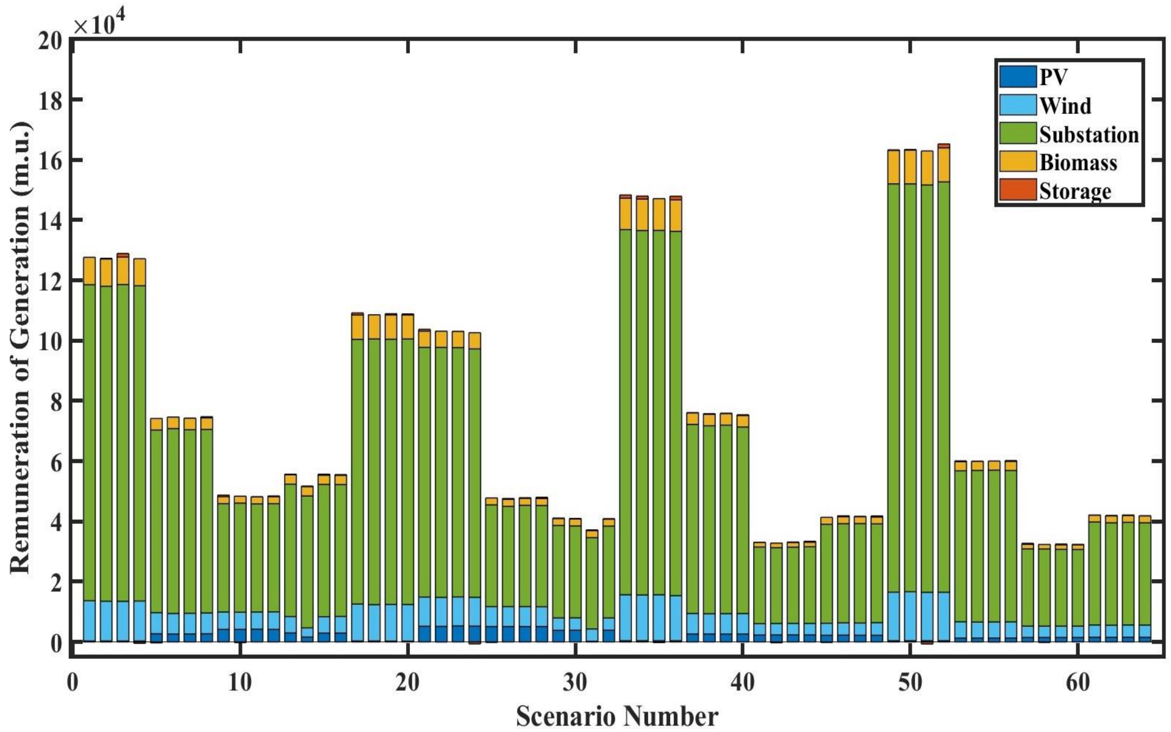

Figure 34 - Remuneration for the 64 sub-scenarios in case study 5

Fig. 34 again reflects the decisions made in Table 15, showing that despite main scenario 9 (sub-scenarios 33 to 36) having lower generated power (Fig. 33), they represent a larger cost remuneration-wise due to that scenario having more total hours.

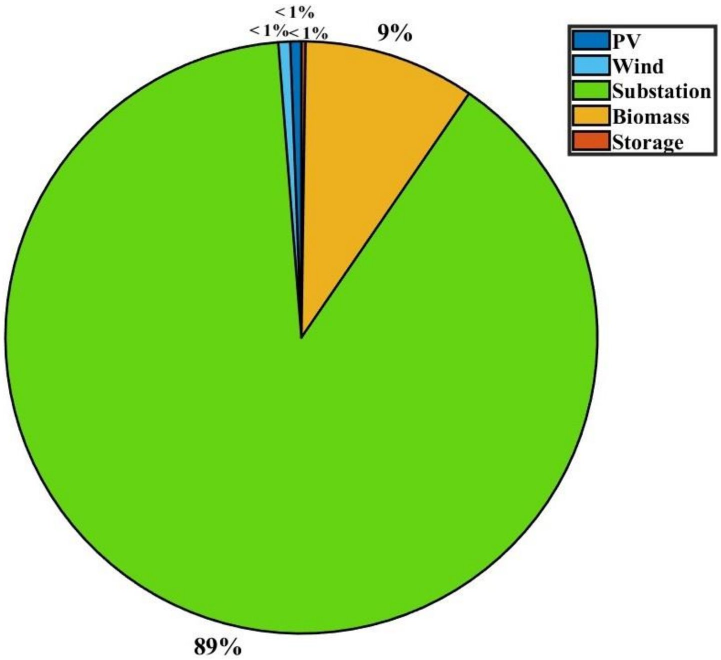

Figure 35 - CO_2 emissions by technology in case study 5

4.7. CHAPTER CONCLUSIONS

This chapter first aimed to outline all the different situations where the optimization model, previously displayed in chapter 3.6. was implemented. These cases studies should not be compared directly, as they are not a direct “evolution” of each other. Instead, they are a development, by considering previously disregarded factors, and a worse economic evaluation is expected by adding some of these factors (risk, remuneration of resources, etc.).

Despite all these different cases studies not being meant to be compared between each other, as mentioned before, even in the most unfavorable situation, where all possible costs are considered (Remuneration of resources and carbon emissions), the economic evaluation still proves valuable, proving why optimal planning is essential. The original network was significantly more expensive even though none of these additional costs were considered because the network configuration was so inefficient. For this reason, even after accounting for resource compensation and carbon emissions, the improved network with the new configuration is still preferable, particularly when it comes to the costs related to generation excess.

Another major difference is the power losses and outage costs, which are significantly reduced with the proposed model since it allows for new installations to the feeder, making the network not entirely dependent on one connection. If that line were to fail, all the networks would lose power, which also translates to more costs associated with distribution, since the power flow is not optimized.

While one test is still missing from this work, being the case where case studies 4) and 5) combine (risk aversion and carbon emission consideration, the test would likely be economically appealing. This test is part of future work plans, as stated in chapter 5.2.

5. CONCLUSIONS

This chapter aims to provide some general conclusions to the thesis, the limitations associated with the work, and the plans for future work.

5.1. FINAL CONCLUSIONS

The significant shift that strives toward a new, cleaner era of electricity generation poses some challenges regarding network planning.

This thesis proposed a novel two-stage stochastic model that aims to capture and intertwine the majority of modern network planning needs.

While vast literature surrounds this topic, they rarely consider all the topics used in the proposed method, such as uncertainty, storage, seasonal variability, remuneration of distributed resources, risk aversion, and carbon emission consideration all at once.

The proposed model was proven to be adequate and makes significant strides forward regarding the optimal planning of networks, especially when highly penetrated by RES.

Accounting for uncertainty is essential in network planning to ensure that the network can adapt to various situations and characteristics. The initial consideration for hourly uncertainty was interesting. However, for case studies 4) and 5), there had to be a decrease to 64 scenarios since the hourly uncertainty was a high computational burden (4 396 743 constraints and 8 987 465 variables).

The remuneration of resources is also necessary since the network's participants must be remunerated appropriately. Alongside that, the consideration for risk aversion is also mandatory. Even if these extreme scenarios have a low probability of occurrence, they need to be considered and accounted for, to plan and adapt the network accordingly to combat these scenarios if they were to occur.

Regarding the choices of lines, all cases chose LXHIO1AV3x185mm^2 for the feeder connections and ACSR 160mm^2 for the remaining normal lines. However, if there were to be a multi-phased investment, this likely would not always be the case, and, as such, this is an aim for future work, as stated in chapter 5.2.

Furthermore, there needs to be consideration for the carbon emissions along the network since the aim is to nullify these values in the future.

In all the addressed study cases there were significant improvements to the SAIDI and SAIFI indices, proving the model to be helpful regarding network topology.

The model proves to be economically appealing in all cases by reducing the costlier scenarios in risk aversion by up to 34% and being profitable even in the most extreme study (case study 5, where all costs are considered, including carbon emissions) by having an NPV of 8 356 240 m.u., a Payback of 4.92 years, and an IRR of 20.26%.

The results suggest that the stochastic method can be used as an efficient approach to deal with the inherent variability of the RES during the seasons of the year and the differences registered in daily periods, while also considering factors such as risk assessment and CO_2 emissions, as well as remuneration of resources.

5.2. LIMITATIONS AND FUTURE WORK

Throughout this thesis's development, the work's main limitation was the computational burden associated with the model, which led to having to adapt the work along the way. This computational burden is mainly due to the size of the network.

Regarding future work, the following is planned:

a) Developing a case study combining risk analysis (CVaR) and carbon emission consideration, which were done only separately thus far;

b) Implementing multi-phased investment as opposed to a single unitary investment in year 0;

c) Applying methods of potentially reducing computational burden, such as decomposition and computational intelligence methods. Future advancements of the work might also not be linear, so linearization methods will be considered.

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