Long-term Active Distribution Network Planning with High Shares of Distributed Energy Resources

Solution methods for planning using realistic large-scale networks

by
David Ulrich Ziegler

supervised by
Prof. Dr. Tomás Gómez San Román
Dr. Carlos Mateo Domingo
Dr. Gianluca Fulli

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Chance favours only the prepared mind - Louis Pasteur

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

David Ulrich Ziegler
Madrid, June 2023

Acknowledgement

We live in some of the most interesting times. On the one hand, we are challenged by multiple crises, a global pandemic, Russia's war on Ukraine and the threats of global instability and climate change. On the other hand, many general developments are also exciting and hopeful, such as empowering scientific and technological breakthroughs and general global development, such as overall less conflict, poverty and hunger. It is important that these seemingly contradictory observations do not lead us to lose hope or, worse, to adopt a fatalistic view of the world. We are often thrown back on our human journey, but we get up and carry on. We know that the sun rises every morning. And so does the hope that we will rise to meet the challenges of our time.

My PhD journey has been an inspiring time, but also challenging at times. Over the last few years I have learnt a lot, both about my research topic and about myself, and I would like to say that I have grown in both areas. This professional and personal growth is largely due to the people who have surrounded me during this time. It has been their guidance, inspiration, feedback and general support that has allowed me to reach this point in my life.

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Abstract

Key to a successful energy transition will be the effective integration of distributed energy resources and new flexibility providers into the energy system. However, the distribution grid, which was built several decades ago to connect transmission lines to end users, was not designed for this purpose. Major changes are therefore needed. Enabling these changes requires a fundamental shift in how electricity distribution systems are designed, operated and planned. At present, there is a lack of comprehensive planning tools to assist operators in their investment planning options. Consequently, reinforcements of conventional network assets are typical solutions implemented. This thesis proposes a set of methodologies to obtain cost-optimal distribution network expansion plans for realistic large-scale networks, using both conventional expansion measures and flexibility contracting from demand response. These methodologies, along with corresponding case studies, are presented sequentially, starting with those for single-stage planning problems, progressing to multistage planning, and finally covering single-stage and multistage planning under uncertainty. The optimisation problem is very complex due to the nonlinearity of the constraints, the combinatorial nature of the problem, the size of the network and the associated number of decision variables. To solve the optimisation problem, the Tabu Search metaheuristic was implemented in the single-stage model, which is the core of all other models. The case study has shown that flexibility can be an efficient alternative to conventional expansion measures, resulting in significant cost savings in single-stage distribution network planning. The multi-stage model is based on a pseudo-dynamic planning approach called forward fill-in. This approach is shown to be effective in accounting for the time value of money and hence cost savings from deferring network investments, as well as the value of flexibility contracts in distribution network planning. Finally, the value of flexibility in distribution network planning under uncertainty is also highlighted, based on the case study using the developed multistage multi-scenario methodology.

Resumen

La clave del éxito de la transición energética será la integración efectiva de los recursos energéticos distribuidos y de los nuevos proveedores de flexibilidad en el sistema energético. Sin embargo, la red de distribución, que se construyó hace varias décadas para conectar las líneas de transporte a los usuarios finales, no se diseñó para este fin. Por lo tanto, se necesitan cambios importantes. Para hacer posibles estos cambios es necesario un cambio fundamental en la forma en que se diseñan, operan y planifican los sistemas de distribución de electricidad. En la actualidad, se carece de herramientas de planificación globales que ayuden a los operadores en sus opciones de planificación de inversiones. En consecuencia, las soluciones típicas que se aplican son los refuerzos de los activos de red convencionales. Esta tesis propone un conjunto de metodologías para obtener planes de expansión de redes de distribución óptimos en costes para redes realistas a gran escala, utilizando tanto medidas de expansión convencionales como la contratación de flexibilidad a partir de la respuesta de la demanda. Estas metodologías, junto con los correspondientes casos prácticos, se presentan secuencialmente, comenzando por las correspondientes a problemas de planificación en una sola etapa, pasando a la planificación en varias etapas y, por último, abarcando la planificación en una sola etapa y en varias etapas bajo incertidumbre. El problema de optimización que nos ocupa es muy complejo, debido principalmente al tamaño de la red y al número de variables de decisión asociadas. Para resolver el problema de optimización, se aplicó la metaheurística de Tabu Search en el modelo de una sola etapa, que es el núcleo de todos los demás modelos. El caso de estudio ha demostrado que la flexibilidad puede ser una alternativa eficaz a las medidas de expansión convencionales, lo que se traduce en un importante ahorro de costes en la planificación de redes de distribución en el modelo de una sola etapa. El modelo multietapa se basa en un enfoque de planificación pseudodinámico denominado forward fill-in. Este enfoque se muestra eficaz para contabilizar el valor temporal del dinero y, por tanto, el ahorro de costes derivado del aplazamiento de las inversiones en la red, así como el valor de la contratación de flexibilidad en la planificación de la red de distribución. Por último, también se pone de relieve el valor de la flexibilidad en la planificación de la red de distribución en condiciones de incertidumbre, basándose en el estudio de un caso práctico en el que se utiliza la metodología multietapa multiescenario propuesta.

Nomenclature

Ω_{br}	Set of all branches
Ω_b	Set of all buses
Ω_{dr}	Set of all buses with contractable flexibility
Ω_{ds}	Set of all distribution substation branches ($\Omega_{ds} \in \Omega_{br}$)
Ω_{fl}	Set of all contractable flexibility types
Ω_{li}	Set of all available power line types for investment
Ω_{pl}	Set of all power line branches ($\Omega_{pl} \in \Omega_{br}$)
Ω_S	Set of all scenarios
Ω_{tra}	Set of all available transformer types for investment
F	Set of contracted flexibility in planning period
F_{p1}	Set of contracted flexibility in period 1
F_{p2}	Set of contracted flexibility in period 2
G	Set of expanded grid components in planning period
G_{p1}	Set of expanded grid components in period 1
G_{p2}	Set of expanded grid components in period 2
P	Set of all periods
T	Set of all expansion policies (policy tree)
br_{ij}	Index of branches
fl	Index of contractable flexibility
i,j	Index of buses
li	Index of power line types
p	Index of period p
s	Index of scenario s

tra	Index of transformer types
$\alpha_{n,r}$	Annuity factor for discounting rate r and lifetime of grid components in n years [%/a]
$A(F)$	Annuity of set F [€/a]
$A(G)$	Annuity of set G [€/a]
$l_{l_{br_{ij}}}$	Length of line at br_{ij} [km]
n	Number of years in planning period
n_p	Number of periods until the planning horizon
n_s	Number of scenarios
n_{p1}	Number of years in planning period 1
n_{p2}	Number of years in planning period 2
r	Discounting rate [%]
$I^{max}_{br_{ij}}$	Maximum allowed current in branch br_{ij} [A]
h	Function representing investment and operational constraints in planning period p
V^{max}_i	Maximum allowed voltage at bus i [kV]
V^{min}_i	Minimum allowed voltage at bus i [kV]
A^{inv}	Sum of all annuities based on investment cost [€/a]
A^{op}	Sum of all annuities based on operational cost [€/a]
$C^{inv}_{li,tot}$	Sum of all investment cost for power lines [€]
$C^{inv}_{tra,tot}$	Sum of all investment cost for transformers [€]
$C^{op}_{fl,tot}$	Sum of all operational cost for flexibility contracts [€/a]
$C^{op}_{li,tot}$	Sum of all operational cost for power lines [€/a]
$C^{op}_{tra,tot}$	Sum of all operational cost for transformers [€/a]
$b_{br_{i,j},li}$	Binary variable indicating line type li investment decision at branch $br_{i,j}$
$b_{br_{i,j},tra}$	Binary variable indicating transformer type tra investment decision at branch $br_{i,j}$
$b_{i,fl}$	Binary variable indicating decision to contract flexibility at bus i

Acronyms

ADN	active distribution network
ADNP	active distribution network planning
DE	deterministic equivalent
DER	Distributed Energy Resources
DG	distributed generation
DN	distribution network
DNP	distribution network planning
DOPF	distribution optimal power flow
DR	demand response
DSO	distribution system operator
ESP	energy system planning
EV	electric vehicle
EVC	electric vehicle charger
GA	Genetic Algorithm
HP	heat pump
HS	heuristic solution
HV	high voltage
ICT	information and communication technology
ILS	Iterative Local Search
LFM	Local Flexibility Markets
LV	low voltage
MA-DN	immunological-system-based memetic algorithm
MCDA	multi-criteria decision analysis
MCS	Monte Carlo simulations

MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MV	medium voltage
NECP	national energy and climate Plans
NPV	net present value
OF	objective function
OPF	optimal power flow
POS	Pareto optimal set
PSO	Particle Swarm Optimisation
PV	photovoltaic
RNM	Reference Network Model
ROA	real option analysis
SA	Simulated Annealing
TS	Tabu Search
VRE	variable renewable energy
WACC	weighted average cost of capital

Contents

1 Introduction

This chapter discusses the motivation for this work and presents the scope, research questions and objectives of this thesis. Finally, the overall structure of the thesis is presented. The motivation starts with a brief consideration of the relevant (geo-)political, regulatory and academic environment. This is followed by an overview of the associated uncertainties relevant to distribution network planning. The motivation then discusses the classical aspects of distribution network planning as well as how upcoming changes in the energy system and technology in general affect the planning of future networks. Finally, a brief overview of network models used in distribution network planning is given.

1.1 Motivation

The ongoing energy transition in response to climate change (European Commission and Directorate-General for Climate Action, 2018) and a rapidly changing global energy security context (European Commission, 2014) requires an unprecedented speed of change in the way the energy system, and in particular the electricity distribution system, is operated and planned (European Commission, Joint Research Centre, et al., 2022; European Commission, 2022a).

In order to achieve a climate neutral European Union by 2050 and to strengthen the EUs competitiveness in sustainable technologies, the European Commission proposed a set of policy initiatives, called the European Green Deal, describing a roadmap to climate neutrality by 2050 (European Commission, 2019). These ambitions have recently been reinforced by the European Commission's REPowerEU initiative, following the unprovoked and unjustified military aggression by the Russian Federation against Ukraine (European Commission, 2022a). One of the objectives of the European Green Deal, is the decarbonisation of the energy sector, the so-called energy transition, which is well on its way nowadays already. In line with this, the European Commission regularly presents general and sector-specific medium- and short-term plans and targets. In addition, Member States periodically define the national strategy and some of the corresponding targets in the national energy and climate Planss (NECPs), which must be consistent with the overall objective of the EU strategy and are to be published every two years covering a ten-year period (European Parliament et al., 2021). In addition to the NECP obligation, Member States are also required by the UNFCCC COP21 agreement to prepare and submit national long-term strategies for 2050 (European Commission and Directorate-General for Climate Action, 2018; Croatian Presidency of the Council of the European Union, 2020). The aim of the long-term plans is to develop strategies for the reduction of greenhouse gas emissions, which must be consistent with the measures set out in the NECP. As greenhouse gas emissions from the energy system account for around 80 % of the EU's total greenhouse gas emissions, strategic energy policy-making plays a crucial role in the European Union's ability to take decisive climate action (European Commission and Directorate-

General for Climate Action, 2018; Commission, 2018). To support this, the scientific community involved in the study of energy systems is crucial to inform policy makers with the knowledge gained from energy system planning (ESP). ESP is a planning exercise that supports both investment and policy decisions in the energy system with typical time horizons of 20 to 50 years. ESP includes many planning subcategories such as generation expansion planning (i.e. planning for electricity generation capacity), transmission expansion planning (i.e. planning for energy transmission networks) and distribution expansion planning (i.e. planning for energy distribution networks), to name a few. There are both semi-quantitative and quantitative ESP models, the latter of which are becoming increasingly important. They can provide valuable decision support in a very complex environment, taking into account uncertain possible future developments. Investment decisions in energy systems mostly concern fixed assets, usually installations with high up-front costs and long lifetimes, often exceeding 40 years. Because these decisions have such a long-term impact and the future is fundamentally uncertain, it is very important to be able to understand the impact of different uncertain futures on decision making in ESP.

1.1.1 Preparing for a changing energy system

For long-term ESP problems, several uncertainties related to energy system modelling and economic decision making are particularly relevant. Fundamentally, these often depend on macroeconomic conditions such as a region's gross domestic product, price stability of and access to primary energy (e.g. crude oil, natural gas, coal, uranium) and critical raw materials (Commission et al., 2017), population, inflation and the cost of capital. As the energy transition proceeds in a simultaneously destabilising global security context (*COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT AND THE COUNCIL 2022 Strategic Foresight Report Twinning the green and digital transitions in the new geopolitical context* 2022), the uncertainty associated with critical raw materials becomes particularly relevant (Pommeret et al., 2022). Uncertainties in ESP that relate to geopolitical developments and related economic impacts can heavily impact prices and availability of energy infrastructure, especially for technologies dependent on critical raw materials (Bach et al., 2017; Centre et al., 2014; Helbig et al., 2018). Though, difficult-to-predict technological breakthroughs reflect uncertainties with potentially very positive impact on the application of new energy technologies (such as energy storage technologies or electric power trains). Such breakthroughs can also counterbalance the risk associated to critical raw material dependency (Centre et al., 2014; Cimprich et al., 2017). These high level uncertainties translate into more specific uncertainties in the application of ESP models. Electric distribution network planning (DNP) is a planning exercise that is part of ESP and is specifically concerned with the electricity distribution system[a]. The most relevant uncertainties affecting DNP are asset costs, future load growth and the degree of decentralisation of variable renewable energy (VRE), i.e. its placement in feeders, voltage levels and unit size (Scheidler, Thurner, et al., 2018), as well as uncertainties arising from the regulatory framework. In DNP, regulatory risks affecting the investment decision making are traditionally related to network investments, but increasingly also to the maturity and durability of emerging parts of the electricity market (e.g. Local Flexibility Markets (LFM), etc.).

[a]In this work, distribution systems, distribution system operator (DSO) and DNP refer only to the electric power system, although other distribution systems are part of the energy system (such as gas distribution and district heating or cooling networks).

In addition to long-term uncertainties, DNP is also subject to short-term uncertainties. This is mainly expressed by the stochasticity of the VRE-based distributed generation (DG), such as from photovoltaic (PV) or wind, as well as short-term uncertainties in the consumption patterns of new load types, in particular electric vehicle chargers (EVCs) and heat pumps (HPs). In long-term ESP, uncertainties and therefore possible future developments are often described in terms of scenarios. In general, scenarios describe possible alternative futures (Bishop et al., 2007; Börjeson et al., 2006). Energy system scenarios project possible future shares of energy generation, consumption, transport, conversion and storage units and their degree of decentralisation, reflecting large long-term uncertainties. In the European Union, many of these scenarios assume high levels of electrification in the transport and heating sectors (European Commission, Directorate-General for Climate Action, et al., 2021). Additionally, electrification became a major focus of policy response to mitigate the threat of Russian gas blackmail (*Statement by the President on the disruption of gas delivery* 2023; European Commission, 2022a). In particular, the electrification of transport and heating is leading to significant load growth on distribution systems due to newly installed loads such as EVCs and HPs (Witte et al., 2020; European Commission, Directorate-General for Climate Action, et al., 2021). These new loads, and possibly DG such as photovoltaic systems as well as distributed storage systems, are known as Distributed Energy Resources (DER). Due to the big choice of technologies in alternative futures, the design phase of energy system scenarios (scenario generation) is critical in order to model the uncertainty well. This is especially true, as variations of different technology options (such as the share of EVCs, HPs and DG), lead to different synergistic or non-synergistic effects between those energy technologies (Troncia et al., 2021). It is important to note the distinction between scenarios and forecasts for the energy system. Scenarios describe a range of possible outcomes based on the underlying uncertainty. Forecasts, on the other hand, try to identify the most likely future outcome or path.

1.1.2 Distribution network planning in the early 21st century

Conventional DNP is the exercise to plan the evolution of the distribution network (DN) into the future, ideally making optimal investment decisions for new network assets, such as substations, transformers or power lines[b]. In its evolution, it has to be made sure that the distribution system is continuously operating and able to accommodate future mixes of DER and their interaction among themselves as well as with higher voltage levels and markets. The optimisation of investment decision-making to accommodate future load growth mainly considers economic objectives based on investment and operational cost, but can also include other objectives such as reliability (Pereira Junior et al., 2013; Muñoz-Delgado et al., 2016), DER hosting capacity (Santos et al., 2017; Zhu et al., 2022) or keeping an adequate level of network losses (Martins et al., 2011; Souza et al., 2011). These can be formulated either as objectives or alternatively as constraints in the problem formulation. The decisions to be made in DNP are about grid capacity, technology choice and investment time. Deterministic single-stage DNP models solve the problem by providing a single set of expansions as the optimal expansion solution for a given network under a given change in network loading (e.g. load and generation growth). In deterministic multistage DNP models, the problem is extended to distribute the set of expansions across the decision stages of the entire

[b] In this thesis, the term power lines refers to overhead power lines (covered or bare conductors) as well as to underground power cables.

planning period, with the network typically also experiencing gradual load and/or DG growth over the planning periods. Optimally distributing expansion measures over decision stages along the periods until the planning horizon is economically imperative, due to the time value of money as well as network asset cost considerations. While the former means that investments made in the future cost less than today, the latter means that supplier industries can provide best prices if their industrial production policies can efficiently leverage economies of scale and relatively steady production and distribution planning. These single and multistage models can of course be extended to include additional aspects of the planning problem, such as multiple objectives or the treatment of uncertainty in the planning period.

Most energy system scenarios for Europe expect a high growth of DER in the power system, particularly EVCs, HPs and DG. Consequently, large-scale integration of DER into the DN raises the need to plan the distribution grid expansion along with the expansion of DG and new loads. The newly added mix of DER and their individual load and generation curves result in new power flow time profiles, from which new peak loading of network assets can be derived (Teichgraeber et al., 2022; Hoffmann et al., 2020). The relevant time slices for planning are those in which the network assets experience peak loading (i.e. peak-load). While peak-load planning has traditionally been concerned only with the network assets' peak loading from load growth, DNs with DG can cause peak loading of network assets due to generation (i.e. reverse power flow). For example, in low voltage (LV) networks, the photovoltaic generation can surpass the local demand, causing a reverse power flow on the power lines to and through the distribution transformer that connects the LV network to the medium voltage (MV)) network. For instance, in a long-term distribution network planning study for ewz, the DSO of the Swiss city of Zurich, reverse power flows due to PV DG are expected to be the main driver for distribution network expansion from 2035 onwards in all scenarios considered (Bader et al., 2016). Other In this work, peak-load planning refers to the predicted peak loading of the network assets, irrespective of the direction of the power flow and therefore the source of the loading (i.e. load or generation). For this combination of peak loading the network must be expanded to provide sufficient capacity at all locations in the network. Sufficient capacity here means that under non-transient steady-state conditions, all network assets remain within their operational limits, namely upper and lower voltage limits as well as maximum permissible current. This expansion of the power DN must be done efficiently to minimise the overall cost for society.

1.1.3 From conventional to non-conventional distribution network expansion

Network expansion measures can comprise conventional expansion of primary equipment capacity (transformers, power lines, etc.) as well as non-conventional expansion using flexibility. Non-conventional expansion measures, sometimes referred to as non-wire alternatives (Contreras-Ocaña et al., 2018), allow the load to be changed temporarily (as in demand response) as well as dynamically adjusting the rated capacity of a conventional asset (as in dynamic line rating) (Energynautics GmbH et al., 2014). The International Smart Grid Action Network (ISGAN) defines flexibility in the context of power systems as "… the ability of power system operation, power system assets, loads, energy storage assets and generators, to change or modify their routine operation for a limited duration, and responding to external service request signals, without inducing unplanned disruptions." (Herndler et al., 2022). In the context of distribution systems, two categories of flexibility options can be defined. On the one hand, flexibility influencing DER behaviour, e.g. by influencing load profiles (Vanthournout et al., 2015; Gils, 2016; Han et al., 2014) or organising DER flexibility through LFM (Valarezo et al., 2021; Gómez et al., n.d.; Gawron-Deutsch et al., n.d.; Kotthaus et al., 2019). On the other hand, power system flexibility can also be provided by advanced control and automation of grid infrastructure equipment, such as decentralised grid automation system, leveraging distribution transformers with on-load tap changers or dynamic line rating of power lines. Using these flexibility options increases the degree of automation and control of the DNs, which turns formerly mostly passive networks into active distribution networks (ADNs). In ADN, grid assets (i.e. decentralised grid automation systems, regulated distribution transformers) and grid-connected components (i.e. DER) are partially actively managed by information and communication technology (ICT) and embedded in measurement, protection and control schemes that enable increased observability and controllability. This increase in observability and controllability of the grid allows for increased integration of DER and efficient coordination of DER behaviour, reduced need for network investment and potentially more resilient operation. ADN planning therefore extends the complexity of conventional planning with additional operational considerations such as the switching of regulation taps of distribution transformers, active and passive feed-in management such as automatic or on-demand curtailment of DG (Schäfer et al., 2020), and the use of the flexibility provided by demand response (DR). Each of these active technologies, if well designed, can defer or even replace conventional network reinforcements (Bolgaryn et al., 2021). Though, these non-conventional technologies usually imply higher operational costs, which deserves further investigation. Generally, from the perspective of cost minimisation is important to understand and benchmark traditional network investment with ADN technologies and solutions, in particular, once DER flexibility is included in the equation. A large-scale grid integration study for the state of Hesse in Germany compares a wide range of flexibility options that show to provide relevant cost saving potential when compared to conventional expansion (Scheidler, Ulffers, et al., 2018). From the operational and planning perspective, the main difference to conventional assets is that the so called *fit and forget approach* is not applicable as those non-conventional expansion measures have to be actively managed, turning relatively passive DNs into ADN, and consequently DNP into active distribution network planning (ADNP) [c]. This also means that, from ADNP's point of view, the value of flexibility depends on the use of flexibility in the operation of the distribution system. From the perspective of investment decision-making, the shorter lifetime of the ICT equipment and the possibility to more frequently reassess the need for contracted flexibility is valuable, especially in the context of high uncertainties in planning exercises. In this thesis, flexibility contracting is defined as the ability of the DSO to contract load flexibility from DR through a third party. That is, it is distinguished between flexibility contracting (i.e. obtaining the ability to use DR reliably as an alternative to asset capacity expansion) and flexibility activation based on contracted flexibility (i.e. the usage of a contracted flexibility resources such as DR in the operational time-frame of a DSO). It is assumed that these contracts are concluded such that the DR service is provided reliably throughout the contracting period (e.g. for 10 years). Therefore, considerations regarding the uncertainty of successful DR provision from loads participating in DR schemes as well as operational and financial considerations

[c]for simplicity, throughout this thesis DNP will be used as a generalisation of ADNP

of DR service provision are beyond the scope of this thesis. From the DSO perspective, the flexibility is contracted as a result of the long-term planning exercise, with possible adoptions in the operational time frames of the DSO.

Interestingly, the European Commission has recently proposed a reform of the EU electricity market design that promotes the use of flexibility from demand response and storage to support cost-effective security of supply and decarbonisation of the energy system (European Commission, Directorate-General for Energy, 2023). The proposed reform requires EU Member States to assess the flexibility needs of their transmission and distribution system operators and to include these projections in Member States' NECPs. The value for money and long-term effectiveness of the various competing network expansion options for network operators are not well understood in terms of the structural, technological and economic assumptions made in the various energy system scenarios (acatech, 2020). As a result, existing expansion options are not fully considered in investment decision making, leading to sub-optimal investment decisions in terms of technology option, capacity and timing of investment. On the one hand, DSOs, who plan, build and operate large electricity DNs, lack concise methods for long-term planning of DN expansion with high penetration of DER, relying mostly on expert assessment. On the other hand, these investment decisions largely depend on the regulative framework, which defines a set of rules under which the DSOs are operating. Therefore, regulators also need concise methods for efficient planning of large-scale DNs with high DER penetration in order to adapt the regulatory framework in such a way that DSOs can be incentivised to make optimal investment decisions in their network expansion planning.

1.1.4 Network models for distribution network planning

Conventionally, due to computational constraints, distribution planning studies could not be undertaken on network models of realistic sizes. Given these limitations, so-called feeder-type networks have often been used, especially for MV and LV networks. Feeder-type networks (also called test-feeders) are synthetic network models that can be derived from real networks, but are usually relatively small in size (Postigo Marcos et al., 2017). Although these models are useful in studies comparing optimisation algorithms and control and protection schemes, their great simplifications significantly limit the accuracy of larger network expansion studies based on them. This is particularly the case for test-feeders with low representativeness, i.e. they do not represent well the specific characteristics of a local network in the context of a particular network study (Postigo Marcos et al., 2017). To overcome these limitations, Reference Network Models (RNMs) are increasingly used for large-scale distribution planning (Mateo, Prettico, et al., 2018; Grzanic et al., 2019), sometimes in combination with realistic networks on the high voltage (HV) level (Büchner et al., 2014). Interestingly, the European Commission's recent support for ENTSO-E and E-DSO to create a digital twin, a sophisticated virtual model of the European electricity system, highlights the value of both real and realistic large-scale network models (European Commission, 2022b). RNMs are large-scale DN models that are highly representative of the real network in a given area, but are synthetic. Such geo-referenced networks are typically built from scratch, using input data such as the distribution of the population and their electricity consumption in a given area, as well as a catalogue of network assets and topological information derived from geographic databases such as OpenStreetMap (OpenStreetMap contributors, 2017).

1.2 Scope, research questions and objectives of the thesis

This thesis treats long-term DNP for realistic large-scale networks in the context of liberalised electricity systems such as those of the EU member states and associates. This context is relevant due to the focus on flexibility, which receives increasing support from policy makers as an efficient alternative to conventional network expansion measures (European Commission, Directorate-General for Energy, 2023). Nevertheless, some of the findings of this thesis can be transferred to other regulatory environments, given their technical nature. Other results would need to be reassessed, especially if different underlying economic parameters and assumptions need to be applied.

As discussed in Section 1.1.3, flexibility contracting as an alternative to conventional network expansion measures has many different characteristics compared to the latter. In this thesis, it is assumed that flexibility contracts are concluded such that the DR service is provided reliably throughout the contracting period (e.g. for 10 years). Therefore, considerations regarding the uncertainty of successful DR provision from loads participating in DR schemes as well as operational and financial considerations of DR service provision are beyond the scope of this thesis. From the DSO perspective, the flexibility is contracted as a result of the long-term planning exercise, with possible adoptions in the operational time frames of the DSO.

The research field related to this scope is wide and moves dynamically, therefore it is important to focus on relevant research questions that can be treated constructively. The main research questions of this thesis are:

- How can non-conventional grid expansion measures such as contracting of load flexibility be modelled in DNP?
- How do multistage planning methods perform in DNP with realistic large-scale systems?
- What is the value of flexibility in long-term DNP?

In order to address the complex problem of long-term ADNP, an incremental approach has been chosen for this thesis. This means that the objectives set out below build constructively on each other.

- The first objective in this thesis is to develop a DNP model that is capable to produce optimal network expansion plans for realistic large-scale networks.
- The second objective is to extend this DNP model to an ADNP model by including flexibility as non-conventional network expansion measure, making conventional and non-conventional expansion financially comparable.
- The third objective is to develop a multistage ADNP model that allocates expansion measures over time. This model should leverage flexibility and help to identify time-dynamic effects in DNP related to non-conventional expansion measures as well as flexibility.
- The fourth and last objective is to develop a methodology for multistage ADNP under uncertainty.

1.3 Thesis outline

Starting with the next chapter, the structure and content of each chapter is briefly described below.

The second chapter presents the state of the art of the literature reviewed on distribution network planning. First, conventional and active distribution network planning are reviewed. This is followed by a meta-review that introduces the most relevant concepts in the scientific literature on distribution network planning. Next, the state of the art of flexibility in distribution network planning is presented. Then, distribution network planning under uncertainty is discussed. Finally, the gaps resulting from the state of the art review are presented.

The third chapter considers single-stage distribution network planning with and without flexibility as an alternative to conventional network expansion measures. First, the problem is defined and a mathematical formulation of the problem is presented. Secondly, a methodology for single-stage distribution network planning based on the Tabu Search metaheuristic is presented as the chosen solution method. A case study is then carried out to demonstrate the capabilities of the developed model on a realistic large scale network. The case study also includes an analysis on a small feeder to illustrate the functionalities of the model. Finally, the results are presented and discussed, and conclusions are drawn.

The fourth chapter considers multistage distribution network planning with and without flexibility as an alternative to conventional network expansion measures. First, the problem is defined and a mathematical formulation of the problem is presented. Secondly, a methodology for multistage distribution network planning based on the pseudo-dynamic forward fill-in method and the model presented in the previous chapter is introduced. A case study is then carried out to demonstrate the capabilities of the developed model. Finally, the results are presented and discussed, and conclusions are drawn.

The fifth chapter discusses how the previously developed models can be extended for distribution network planning under uncertainty. First, an overview of uncertainty and risk relevant to distribution network planning and related solution methods is given. Then, the problem formulation and a solution method for single-stage multi-scenario distribution network planning are presented. Subsequently, the problem is extended to multistage multi-scenario distribution network planning and a corresponding problem formulation and solution method is presented. Thereafter, a case study on robust two-stage two-scenario DNP is presented. Finally, the results are discussed and conclusions are drawn.

The sixth chapter, as the last chapter of the thesis, brings the work presented to a close. Firstly, the conclusions are discussed. Secondly, the contributions of this thesis are presented. Finally, promising future work in distribution network planning is presented.

2 State of the art

This chapter presents the state of the art of the reviewed literature on distribution network planning. The first section reviews conventional and active distribution network planning. This is followed by a meta-review section that introduces the most relevant concepts in the scientific literature on distribution network planning. A third section presents the state of the art of flexibility in distribution network planning. Distribution network planning under uncertainty is discussed in the second to last section. Finally, the gaps resulting from the state of the art review are presented.

2.1 Conventional and active distribution network planning

As discussed in Section 1.1, electric distribution networks and their operators are facing significant challenges in the decades ahead. The large-scale integration of DER being the main driver for change, both in DN operation and planning.

DNP has been studied in the scientific literature since the early 1970s. Traditionally, the focus has been on substation expansion and conventional reinforcements. More recently, with the increasing penetration of DER, ADNs and their planning have also received more attention, not only from academia and industry, but also from policy makers (European Commission, 2022b).

In conventional long-term DNP, the investment decisions to be made depend roughly on the existing network and the expected load growth. Greenfield planning in general and some brownfield planning may involve decisions on the optimal location of substations, the location and number of feeders and their design, the optimal load and substation capacity allocation, and the optimal transformer mix per substation. Brownfield planning, which is less often concerned with the siting and sizing of EHV/HV or HV/MV substations, is mostly concerned with decisions on technology selection, network capacity, installation and investment time. Deterministic single-stage DNP models solve the problem by providing a single set of expansions as the optimal expansion solution for a given network under a given change in network load (e.g. load and generation growth). This is the simplest single-stage model, which can of course be extended to include additional aspects of the planning problem, such as multiple objectives or the treatment of uncertainty in the planning period.

The optimisation of investment decision making to accommodate future network loading mainly considers economic objectives based on investment and operational cost, but can also include other objectives turning the single-objective DNP problem into a multi-objective one. Such DNP problems with multiple objectives are often optimising additional objectives such as reliability (Pereira Junior et al., 2013; Muñoz-Delgado et al., 2016) or DER hosting capacity (Santos et al., 2017; Zhu et al., 2022). In principle, multi-objective problems can be solved in two ways. One way is to formulate all objectives in the same unit (e.g. €), which allows summation of the individual objective function terms, and solve the problem using a single-objective solution method, obtaining only one optimal solution. In this case, before summing the individual objective function terms, they can also be weighted with some factors expressing the decision maker's preferences. Another way is to solve the multi-objective problem using the solution method of multi-objective optimisation. This method produces a set of optimal solutions that describe optimal solutions for a set of combinations of the multiple objective function terms, called the Pareto optimal set. The decision maker can then select a preferred solution from this set, based on the preferences for each objective, or use a sequential decision method to do so. For the latter approach, an interesting example is provided by (Muñoz-Delgado et al., 2019), where stochastic programming to incorporate uncertainty in load, PV and wind generation is combined in a Mixed-Integer Linear Programming (MILP) optimisation to compute candidates for which a predictive reliability assessment is subsequently performed. This approach provides the planner with a set of cost-effective candidate solutions that meet reliability expectations.

Historically, conventional distribution planning has been carried out for two basic conditions, normal operational conditions and emergency conditions (Khator et al., 1997). Normal operational conditions are those non-transient steady-state conditions in which no fault caused network assets to operate outside their standard operational limits and no emergency intervention (e.g. load shedding or network reconfiguration) has adopted the load and generation balances to accommodate the load flows in the network. Network assets are designed to operate the large majority of the time in normal operational conditions, remaining within the respective physical limits. Those limits for assets in non-transient steady-state conditions are upper and lower voltage limits and maximum permissible current. Besides the limits of individual network assets, normal operational conditions also assure that all network assets as well as all loads, generators and storage units are fully connected and operational as planned. Planning under emergency, commonly referred to as the study of reliability or resilience, considers the possibility of failures of network assets, such as transformers, power lines or switches. In other words, the aim of DNP under emergency is to plan the network in such a way that a certain number of network faults can be handled by the network operator for example by reallocating feeders in substations, reconfiguring the network or, in the worst case, by load shedding. In this work, the focus lies on planning under normal operational conditions, which is here considered as DNP.

There are two general types of solution methods for optimal DNP. The first is mathematical optimisation, which can guarantee the optimality of the results, although complex problems may not be computationally tractable with this approach. In such cases, problem simplification techniques to handle the computational complexity of distribution grid expansion planning models like problem decomposition, constraint relaxation or stopping the search process early once a feasible solution is found, are often applied. The second type includes clustering techniques as well as (meta-) heuristic algorithms, which are often used when the computational time of mathematical programming based models reaches its limits (Quintana et al., 1993; Talbi, 2009). Metaheuristics are generalised heuristic optimisation methods, often inspired by nature, that do not guarantee optimality but can produce good results for hard problems. Therefore, they are usually classified as part of the family of approximate optimisation algorithms. (Talbi, 2009). Such algorithms, as mathematical programming based approximate optimisation in (Aoki et al., 1990) and knowledge-based expert systems in (Hsu et al., 1990), have a long history in operations research and specifically in conventional DNP often included alongside Artificial Intelligence approaches (Miranda, Ranito, et al., 1994; Glover, 1986). Population-based and single-solution based algorithms are two types of distinguishable metaheuristic algorithms (Miranda, Ranito, et al., 1994; Talbi, 2009; Gendreau et al., 2019). Genetic Algorithms (GAs) (Miranda, Ranito, et al., 1994; Camargo et al., 2013) and Particle Swarm Optimisation (PSO) (Ganguly et al., 2011) are common examples of population-based metaheuristics. Tabu Search (TS), Simulated Annealing (SA) and Iterative Local Search (ILS) are common single-solution based metaheuristic algorithms (Gendreau et al., 2019; Héliodore et al., 2017).

Multistage DNP models provide the sets of expansion measures along multiple planning periods each of which experiences load growth as well as potentially growth of DER. In this thesis the two planning types of multistage DNP models are referred to as dynamic and pseudo-dynamic multistage planning, in line with the common classification of multistage methods (Gönen et al., 1986; Ramirez-Rosado and Gonen, 1991). In dynamic DNP, all time-dynamic effects between the planning periods are captured by the model, allowing to find an optimal solution for the multistage DNP problem (Gonen et al., 1987). Dynamic planning models either solve the multistage problem entirely or decompose the problem, taking care of the time-dynamic effects using various methods. Among these methods, some are based on graph theory (Popović et al., 2010; Vaziri et al., 2001), and another applies Real-Option Valuation for planning with flexibility from DG (Samper et al., 2013). Among the dynamic planning models, some solution methods are based on mathematical programming (Vaziri et al., 2001; Haffner et al., 2008; Muñoz-Delgado et al., 2019). Others use meta-heuristics to solve the multistage DNP problem, apply variations of GA (Miranda, Ranito, et al., 1994; Naderi et al., 2012; Nejadfard-Jahromi et al., 2015), PSO (Samper et al., 2013) or TS (Pereira Junior et al., 2013). Pseudo-dynamic planning models, on the other hand, can not capture all time-dynamic effects between the stages, which leads to sub-optimal results. Nevertheless, even the later models can provide valuable insight into a given planning problem. Well-known pseudo-dynamic methods are forward fill-in (Khator et al., 1997; Ravadanegh et al., 2013; Ravadanegh et al., 2014; Saboori et al., 2015), backward pull-out (Sun et al., 1982; Ramirez-Rosado and Gonen, 1991; Quintana et al., 1993; Falaghi et al., 2011) as well as more advanced methods with different forms of backward-forward iterations (Nara et al., 1991; Borges et al., 2012) or so-called heuristic interlacing of single stage solutions (Tang, 1996). The forward fill-in approach consists of consecutively executing a single-stage planning model (e.g. based on TS), while load and/or DG growth is applied between the stages. That is, the load growth of period one is applied to the initial network, followed by a run of the single-stage expansion model. The load growth of the second period is then applied to the resulting network, followed by the second run of the single-stage expansion model and so on, until the year of the planning horizon is reached. The backward pull-out approach consists of two phases. In the first phase, the DNP is solved for the peak-load conditions at the planning horizon, determining the optimal set of expansions in this last stage of the multistage problem. Thereafter, this set of optimal expansions is distributed along the planning stages by consecutively solving a single-stage DNP problem, as in the forward fill-in method but constrained to the set of expansions found in the first phase of the backward pull-out method. In a variation of backward pull-out, which could be termed backward fill-in, the DNP problem is solved for the peak-load condition at the horizon year, from where the determined optimal set of expansions is distributed backwards in time, starting at the year of the planning horizon (Koutsoukis et al., 2018).

2.2 Meta-review on distribution network planning

A significant number of review papers on conventional and ADN planning have recently already been published (Ganguly et al., 2013; Georgilakis et al., 2015; Resener et al., 2018; Xiang et al., 2016; Jordehi, 2015). Those reviews use various sets of characteristics for classification that are briefly described in the following. Table 2.1 shows an overview of the characteristics considered in the review papers.

While different *objectives* such as minimisation of system losses, enhancement of reliability, and minimisation of environmental impact or cost-effective DER integration can be defined in distribution planning, the most significant objective of the optimisation is typically a total cost minimisation.

The *objective type* describes whether an objective function is formulated as single-objective or multi-objective. Solutions of multi-objective optimisation provide an optimal solution in the form of a Pareto optimal set. The different objectives can then be weighted ex-post, to identify the preferred solution. If the weighting of the individual objectives is known in advance, a single-objective function can be formulated in which each objective is formulated as an explicit mathematical term.

Decision variables, such as the location and/or size of substation, feeder, reclosers, storage systems, EVC and DG, are among the most frequently used classifiers in the analysed review papers (Georgilakis et al., 2015; Jordehi, 2015; Resener et al., 2018; Xiang et al., 2016).

The *planning type* is a characteristic that differentiates between single-period or static models and multi-period or multistage models (Georgilakis et al., 2015; Jordehi, 2015; Resener et al., 2018; Xiang et al., 2016). The former formulates the problem with all its variables and constraints to find an optimal solution for a single time period, while the latter considers the evolution of the distribution system over time, potentially delivering optimal investment decisions at multiple time steps of a planning period. Often, multistage planning approaches are structured into two groups. The first group is specified as pseudo-dynamic multistage planning. Methods based on this planning type deliver investment or expansion decisions at each time step of the multiple periods by solving multiple single-stage problems successively. In planning types of the second group, decisions are optimised over the entire planning period, while producing investment or expansion decisions for each time step or stage. (Ganguly et al., 2013) define this group as dynamic planning, while (Jordehi, 2015; Resener et al., 2018) define it as simultaneous multistage planning. Due to the increased complexity and the related computational effort, most reviewed multistage optimisation approaches consider only few stages.

The *planning duration* or time horizon as a classification characteristic is only used by (Jordehi, 2015). Similarly, (Resener et al., 2018) specifies operation planning as planning without time horizon in the future (t=0) and categorise expansion planning in short-term planning (1-4 years) and long-term planning (4-20 years) (Resener et al., 2018) or (> 4 years) (Ganguly et al., 2013). Outside of the review papers, but still relevant is the definition of horizon planning for planning horizons beyond 20 years (Fletcher et al., 2007).

Whether and how *uncertainty modelling* is considered in the reviewed work, is used as a characteristic by (Ganguly et al., 2013) and (Xiang et al., 2016). (Resener et al., 2018) is classifying the models by the so-called *environment of the model*, which describes if the model contains deterministic elements, stochastic elements or a mix of stochastic and deterministic elements.

Reliability as a characteristic for model classification is introduced by (Ganguly et al., 2013), though all review papers discuss reliability of power distribution systems. Generally, two main approaches exist to consider reliability in distribution planning (Ganguly et al., 2013). In one approach, an additional objective function is added to planning under normal conditions, creating a multi-objective problem. The other approach uses predefined fault or contingency conditions as model inputs, while the planning problem remains a single-objective optimisation.

Greenfield vs. Brownfield is a characteristic that describes whether a new network is created from scratch (greenfield), an existing network is expanded (brownfield), or a combination of the two. This feature is used under different names by (Georgilakis et al., 2015; Xiang et al., 2016).

The *network model* characteristics helps differentiating between different complexities of the modelled electric distribution system model. Authors either just differentiate network models used by primary and secondary distribution (Georgilakis et al., 2015) or more detailed by the number of nodes on voltage levels, number of customers or IEEE standard type feeders used (Jordehi, 2015).

The used *load model*, such as constant or variable load and probabilistic or three-level load curves, is a characteristic introduced by (Jordehi, 2015).

To solve conventional DNP problems, various methods based on mathematical programming as well as heuristics and metaheuristics have been taken. While some of the authors classify the overall optimisation approach as *optimisation method* (Georgilakis et al., 2015; Jordehi, 2015; Resener et al., 2018), others divide the later into *mathematical formulation* and *solution method* (Ganguly et al., 2013; Xiang et al., 2016). The mathematical formulation describes how the objective function (OF) of the optimisation approach is formulated. That is, whether it contains any or multiples of linear and non-linear terms, continuous and discrete formulations, and stochastic elements. In addition, constraints on the optimisation problem are part of the mathematical formulation.

None of the authors of the review papers use flexibility modelling as characteristic for benchmarking DNP publications. One of the review papers discusses flexibility in DNP in combination with related future research trends (Resener et al., 2018). Another review paper discusses controllable devices generically in the context of operational optimisation and their impact on the and planning problem (Xiang et al., 2016). Considering ADN components in the reviewed and planning publications, (Georgilakis et al., 2015) list planning publications and the respectively modelled active components. Active components that can be summarised as flexibility are DR, load control and DER control. Also, more generically, loads are distinguished as elastic or non-elastic in ADN load model formulation. (Jordehi, 2015) find that demand side management has not been taken into consideration in the reviewed DNP problems. Flexibility is not discussed in general in (Ganguly et al., 2013), though DR (i.e. load dependent electricity price) is once mentioned in reference to a reviewed paper.

	Resener et al. 2018 Resener et al., 2018	Xiang et al. 2016 Xiang et al., 2016	Georgil. et al. 2015 Georgilakis et al., 2015	Jordehi 2015 Jordehi, 2015	Ganguly et al. 2013 Ganguly et al., 2013
Objectives	✓	✓	✓	✓	
Objective types	✓				✓
Decision variables	✓	✓	✓	✓	
Planning type	✓	✓	✓	✓	
Planning duration				✓	
Uncertainty modelling		✓			✓
Environment of the model	✓				
Reliability feature					✓
Greenfield vs. Brownfield		✓	✓		
Network model			✓	✓	
Load model				✓	
Optimisation method	✓		✓	✓	
Mathematical formulation		✓			✓
Solution method		✓			✓

Table 2.1: Characteristics used for various classifications by review papers

2.3 Review on distribution network planning treating flexibility

The energy transition to a cleaner and more sustainable society requires a transformation in the design, operation and planning of the power system to accommodate the high penetration of DER at the distribution level. However, the distribution grid that was set up several decades ago to connect transmission lines to end users was not designed for this task. Major changes are therefore needed. As mentioned in Chapter 1.1, several options can be considered, the value and long-term effectiveness of which has not yet been assessed under different energy system scenarios (acatech, 2020). Consequently, today, existing technology options such as load flexibility through DR or demand side management are not fully considered in investment decision making, leading to non-optimal investment decisions with respect to expansion technology option, capacity, and timing of the investment.

A large number of papers treating DNP and some type of flexibility, such as from loads, generation or storage, have been reviewed. The twelve most relevant of those are analysed in this section in greater detail, and classified in Table 2.2. Publications that present general planning frameworks, DG or DER hosting studies or papers that are focused on energy system scenario studies, have not been included in this review. Of the reviewed papers, there are only few publications with DNP models that incorporate load flexibility, and none of them presents a validation of the model by a case study on a realistic large-scale network. Of those reviewed papers, seven apply some type of load flexibility as non-conventional expansion measure (e.g. DR, EV smart charging, etc.) (Abdi-Siab et al., 2020; Arasteh et al., 2016; Bin Humayd et al., 2017; Celli et al., 2008; Xie et al., 2020; Xing et al., 2016; Zeng et al., 2016); six apply flexibility from DGs (e.g. DG dispatch, DG curtailment) (Celli et al., 2008; Haesen et al., 2009; Karagiannopoulos et al., 2016; Koutsoukis et al., 2018; Xing et al., 2016; Zeng et al., 2016); three apply flexibility from storage (e.g. EV including vehicle-2-grid, distributed energy storage systems, etc.) (Saboori et al., 2015; Shen et al., 2018; Xing et al., 2016). Regarding the solution method for the DNP problem, six of the reviewed papers use mathematical programming (Abdi-Siab et al., 2020; Bin Humayd et al., 2017; Karagiannopoulos et al., 2016; Shen et al., 2018; Xie et al., 2020; Xing et al., 2016), one of them in combination with a heuristic method (i.e. combining optimal power flow (OPF) with a heuristic) (Karagiannopoulos et al., 2016). The other five papers use metaheuristics (Arasteh et al., 2016; Haesen et al., 2009; Koutsoukis et al., 2018; Saboori et al., 2015; Zeng et al., 2016), one of those in combination with a numerical method to solve the distribution optimal power flow (DOPF) (Haesen et al., 2009), and one paper uses a heuristic method (Celli et al., 2008). Most of the papers use a feeder-type network model, while two use a real network model (Celli et al., 2008; Koutsoukis et al., 2018), obtained from DSOs. The number of buses in the network models of the reviewed publications ranges from 18 to 355. While all papers model the MV level, some include network elements of the LV level (Celli et al., 2008; Karagiannopoulos et al., 2016) or HV level (Celli et al., 2008; Xing et al., 2016; Zeng et al., 2016). Only one paper includes all three voltage levels, though only 118 buses are included, based on a real network, and the solution method used is a simple heuristic (Celli et al., 2008).

Reference	Load flexibility	Generation flexibility	Storage flexibility	Mathematical programming	Metaheuristic	Optimisation method	Network model	No. of buses	HV modelled	MV modelled	LV modelled
A	✓			✓		MILP	feeder-type	24		✓	
B	✓				✓	MO-PSO[a]	feeder-type	33		✓	
C	✓			✓		MINLP[b]	feeder-type	69		✓	
D	✓	✓				heuristic	real network	118	✓	✓	✓
E		✓			✓	SPEA2[c] & DOPF[d]	feeder-type	355		✓	
F		✓		✓		heuristic & OPF[e]	feeder-type	27		✓	✓
G		✓			✓	GA	real network	267		✓	
H			✓		✓	PSO	feeder-type	30		✓	
I			✓	✓		MILP	feeder-type	18		✓	
J	✓			✓		SOCP[f]	feeder-type	122		✓	
K	✓	✓	✓	✓		SOCP	feeder-type	50	✓	✓	
L	✓	✓			✓	GA	feeder-type	33	✓	✓	
This thesis	✓				✓	TS	realistic large-scale network	2762	✓	✓	✓

Table 2.2: Reviewed DNP papers treating flexibility, their methods and network modelling, References: A: (Abdi-Siab et al., 2020), B: (Arasteh et al., 2016), C: (Bin Humayd et al., 2017), D: (Celli et al., 2008), E: (Haesen et al., 2009), F: (Karagiannopoulos et al., 2016), G: (Koutsoukis et al., 2018), H: (Saboori et al., 2015), I: (Shen et al., 2018), J: (Xie et al., 2020), K: (Xing et al., 2016), L: (Zeng et al., 2016)

While relatively small feeder-type network models are convenient for many DNP studies, they have various limitations. Their representativeness in large areas with diverse socio-economic and technical characteristics can be limited, especially when large-scale grid modernisation is expected. Also, their value and accuracy with respect to benchmarking of advanced optimisation algorithms such as network reconfiguration, Volt/Var optimisation, etc. is limited (González et al., 2012). Finally, feeder-type models usually lack geographical information, which limits their meaningfulness in topological studies on reconfiguration as well as for resilience studies in the wake of natural disasters. Self-explanatory, real network models do not incorporate these constraints, though they can mostly not be used in public research, due to their confidentiality as they are considered critical infrastructure (Postigo Marcos et al., 2017). Therefore, realistic network models can be an effective alternative to confidential real network models, while also overcoming the limitations of the feeder-type models (Mateo, Postigo, et al., 2020; Palmintier et al., 2021).

2.4 Review on distribution network planning under uncertainty

As discussed in Section 1.1.1, long-term DNP faces significant uncertainties in the decades ahead. Therefore, a review of DNP under deep uncertainty is presented in the following.

A large number of papers on DNP under uncertainty have been reviewed. In order to group these papers according to the logic of Chapter 5, the main distinction that can be made is whether they are concerned with single-stage planning or with multistage planning.

Of the six most relevant papers dealing with single-stage planning, four model uncertainty probabilistically (Souza et al., 2011; Munoz-Delgado et al., 2021; Mehrjerdi et al., 2020; Carrano et al., 2007), and two possibilistically (Ramirez-Rosado, Dominguez-Navarro, et al., 1999; Ramirez-Rosado and Domínguez-Navarro, 2004). Possibilistic models are used when probabilities or probability distributions are not available or cannot be reasonably derived for the uncertainty considered in the particular DNP problem.

The earliest paper applies TS to DNP under uncertainty in node demand and expansion costs (Ramirez-Rosado, Dominguez-Navarro, et al., 1999). The possibilistic uncertainties are modelled using fuzzy triangular sets, where each value of the set represents a scenario. Based on these uncertainties, the possibilistic objective function is modelled, including the operational constraints of the network, which represent possibilistic power flows. The model considers the robustness, or exposure as in risk acceptance, of the studied solutions by the α-cut of the fuzzy triangular load set. In a later paper, the two main authors expand the model to multi-objective DNP considering the objectives of cost, reliability and exposure (Ramirez-Rosado and Domínguez-Navarro, 2004). The multi-objective model produces a set of non-dominated solutions which is normalised and a maxi-min method applied to select the best candidate based on the planners preferences. For both

[a] MPSO - Multiobjective PSO

[b] MINLP - Mixed Integer Non-Linear Programming

[c] SPEA2 - (improved) strength pareto evolutionary algorithm (Zitzler et al., 2001)

[d] DOPF - solved here using backward-forward sweep as numerical method to solve the OPF problem for radial distribution systems with sufficient precision

[e] OPF - here solved using mathematical programming (within MATPOWER)

[f] SOCP - Second Order Cone Programming

of these papers some doubt remains on whether the fuzzy modelling captures and represents the related uncertainty well, especially in the context of long-term DNP.

As an alternative to possibilistic modelling of uncertainty, the following authors of single-stage DNP model uncertainty probabilistically (Carrano et al., 2007). A GA-based approach takes into account the uncertainty of load growth as well as a so-called "energy tax" (i.e. the cost of energy supplied at each node). The node load uncertainty is modelled using known probability distributions, which are used by MCS to generate a large set of scenarios. Based on the scenarios provided, the DNP method is then used to generate an optimal solution of the mean scenario as well as a set of suboptimal ones close to it. Finally, a multi-objective sensitivity analysis is performed, taking into account cost and reliability. The efficiency of the set of solutions (i.e. based on cost and reliability) is evaluated using dominance analysis, they are filtered for infeasibility and an expert selects the best solution. While the approach to compute a set of solutions followed by their evaluation against all generated scenarios seems generally interesting, some doubt remains whether the solutions generated around the mean scenario are diverse enough to provide good solutions when the DNP problem is faced with deep uncertainty.

The papers on single-stage DNP under uncertainty presented above, have all considered reliability of some form in their approach (Ramirez-Rosado, Dominguez-Navarro, et al., 1999; Ramirez-Rosado and Domínguez-Navarro, 2004; Carrano et al., 2007). The following three papers do not consider reliability as a objective in their single-stage DNP methodology (Souza et al., 2011; Munoz-Delgado et al., 2021; Mehrjerdi et al., 2020). Though, the DNP model based on an immunological-system-based memetic algorithm (MA-DN) considers cost of losses as an objective (Souza et al., 2011). That paper models nodal uncertainty of demand evolution and energy tax based on probability distributions processed into scenarios using MCS followed by a multi-objective sensitivity analysis, as in the approach described above (Carrano et al., 2007). While this paper extends the size of the network model used from 21 to 100 buses, the scalability to realistic large scale distribution networks has not been demonstrated. Two of the single-stage papers presented in Table 2.3 use scenario-based stochastic programming as an approach to DNP under uncertainty, and also consider non-conventional expansion measures (Mehrjerdi et al., 2020; Munoz-Delgado et al., 2021). The first one of these uses DER (i.e. wind power and hydrogen storage) siting and sizing as non-conventional expansion alternative while considering wind generation uncertainty modelled using a normal distribution (Mehrjerdi et al., 2020). Before solving the stochastic MILP in GAMS, a large set of scenarios is generated by MCS followed by a scenario-reduction technique called *backward-scenario reduction*. The second one of those papers using stochastic programming is concerned with integrated transmission and distribution planning, where the authors consider HV level as transmission, as opposed to this thesis (Munoz-Delgado et al., 2021). The uncertainty formulated in scenarios is transferred into a MILP deterministic equivalent (DE) and solved using GAMS. This paper considers load and wind stochasticity based on historical data and combines this short-term uncertainty with long-term uncertainty of load growth in multiple scenarios. In one of two case studies, the model applies investment in wind-based DG as a non-conventional expansion measure, finding that substantial investment savings can be made. The solution method used in both of the previously discussed papers (Mehrjerdi et al., 2020; Munoz-Delgado et al., 2021) is based on mathematical programming, which raises doubts on the scalability of the approach to realistic large-scale networks. Of those papers on single-stage DNP under uncertainty shown in

Table 2.3, the largest network model consists of 334 buses on HV and MV level (Munoz-Delgado et al., 2021).

Reference	Probabilistic	Posssibilistic	Short-term uncertainty: load	Short-term uncertainty: DG	conv. expansion	non-conv. expansion	Mathematical programming	Metaheuristic	Optimisation method	Multi-objective	No. of buses	HV modelled	MV modelled	LV modelled
A	✓		✓		✓			✓	MA[g]	(✓)	100		✓	
B		✓	✓		✓			✓	TS		182		✓	
C		✓	✓		✓			✓	TS	✓	182		✓	
D	✓		✓		✓			✓	GA	✓	21		✓	
E	✓		✓	✓	✓	✓	✓		MILP		33		✓	
F	✓		✓	✓	✓	✓	✓		DE[h]		334	✓	✓	

Table 2.3: Reviewed single-stage DNP papers treating long-term uncertainty, their methods and network (expansion) modelling. References: A: (Souza et al., 2011), B: (Ramirez-Rosado, Dominguez-Navarro, et al., 1999), C: (Ramirez-Rosado and Domínguez-Navarro, 2004), D: (Carrano et al., 2007), E: (Mehrjerdi et al., 2020), F: (Munoz-Delgado et al., 2021)

Of the five most relevant papers dealing with multistage planning, the most recent two model uncertainty probabilistically (Wang et al., 2011; Muñoz-Delgado et al., 2016) and the older three possibilistically (Skok et al., 2005; Haghifam et al., 2002; Carvalho et al., 2000). The earliest paper proposes a new solution method for multistage greenfield DNP under uncertainty (Carvalho et al., 2000). Uncertainty in load growth and expansion costs is modelled using weighted scenarios. The presented method hedges the first-stage decision against later-stage uncertainty by incorporating later-stage information from the scenario tree into the first-stage decision process. The proposed hedging algorithm is suggested to work well with evolutionary algorithms, although it is not clear on which evolutionary algorithm the two-stage planning case study is based. Also, the case study is applied only for a MV network with 20 buses. Another paper proposes a pseudo-dynamic method for multistage DNP under uncertainty (Haghifam et al., 2002). The embedded single-stage DNP model is based on GA and the pseudo-dynamic approach is backward fill-in. The DNP problem aims at the optimal siting and sizing of HV/MV substations, although the practicality of feeder routing as well as the applicability and scalability to realistic large scale networks is unclear. The model takes into account the cost of substation and feeder expansion, as well as losses. Short- and long-term load uncertainty is modelled using fuzzy set theory. The last of the three papers using

[g] MA-DN for DNP
[h] MILP formulated as DE

possibilistic uncertainty modelling is a pseudo-dynamic multi-objective, multistage DNP based on two interacting evolutionary algorithms that optimise for cost and reliability (Skok et al., 2005). Even though the title indicates "dynamic" planning, the method applied is based on the pseudo-dynamic approach backward pull-out. Here, one evolutionary algorithm produces the horizon plan, which is then processed by the second evolutionary algorithm to distribute the expansions along the planning stages. Load and DG short-term and long-term uncertainties as well as reliability indices and economic parameters are modelled by fuzzy numbers. Fuzzy constraints and fuzzy power flows are used consistently, allowing the use of a robustness criterion when evaluating candidate solutions, though the same concerns about practical relevance of fuzzy modelling as previously discussed can be raised (Ramirez-Rosado, Dominguez-Navarro, et al., 1999; Ramirez-Rosado and Domínguez-Navarro, 2004).

Reference	Probabilistic	Possibilistic	Short-term uncertainty: load	Short-term uncertainty: DG	conv. expansion	non-conv. expansion	multistage approach	Mathematical programming	Metaheuristic	Optimisation method	Multi-objective	No. of buses	HV modelled	MV modelled	LV modelled
A		✓			✓		D[i]		✓	EA[j]		20		✓	
B		✓	(✓)		✓		PD[k]		✓	GA	(✓)	34		✓	
C		✓	✓	✓	✓		D[l]		✓	EA[m]	✓	246		✓	
D	✓				✓		PD[n]		✓	GA		16		✓	
E	✓		✓	✓	✓	✓	D[o]	✓		DE[p]	✓	138		✓	

Table 2.4: Most relevant reviewed multistage DNP papers treating long-term uncertainty, their methods and network (expansion) modelling. References: A: (Carvalho et al., 2000), B: (Haghifam et al., 2002), C: (Skok et al., 2005), D: (Wang et al., 2011), E: (Muñoz-Delgado et al., 2016)

Among the papers on multistage DNP that model uncertainty probabilistically, one is for multistage Greenfield DNP under uncertainty, based on a modified GA (Wang et al., 2011). Here, the long-term load uncertainty is modelled in scenarios with probabilities to be assigned by an expert planner. The pseudo-dynamic method *forward approach* (forward fill-in) is used as multistage

[i] Dynamic: Hedging second stage decisions into first stage decision using GA)

[j] an EA is combined with a hedging algorithm

[k] Pseudo-dynamic: horizon year + forward-fill-in

[l] Pseudo-dynamic: in each iteration a horizon plan and consecutively on optimal expansion plan, distributing the expansion decisions along the stages

[m] a combination of two EA is used

[n] Pseudo-dynamic: forward-fill-in (2-stage)

[o] Dynamic: based on mathematical programming

[p] MILP formulated as DE

planning technique. A balanced GA is used to generate plans for multiple scenarios, followed by (modified) data envelopment analysis to select from the set. Specifically, in the case study at hand, the process is as follows. To represent the uncertainty of the first stage, a set of 50 expansion plans is generated, one for each scenario. From these 50, the best 5 are selected as candidates for the second stage. Based on these 5 candidates, a second run of the DNP algorithm is performed, generating a total of 250 expansion plans, which are then evaluated for both economic performance and robustness. The large number of expansion plans necessary, combined with the small number of only 16 buses in the network model, creates doubts about the scalability of the model. The other paper that models uncertainty probabilistically is a multi-objective, dynamic multi-stage DNP model that uses probability distributions based on historical data (Muñoz-Delgado et al., 2016). The model uses scenario-based stochastic programming to incorporate the uncertainty of load, PV and wind generation into a DE-MILP problem to compute candidates, for which a predictive reliability assessment is then performed. As a result, the distribution planner receives a set of cost-effective candidate solutions that meet the planner's reliability expectations. The model considers conventional expansion (i.e. transformers, lines, substations) and non-conventional expansion (i.e. wind/PV/conventional DG installation) measures, but only considers 138 buses in the network model.

Of those papers on multistage DNP under uncertainty the largest network model consists of 246 buses (Skok et al., 2005) and all network models only consider the MV level, as shown in Table 2.4.

2.5 Gaps in the state of the art

Single-stage DNP using conventional expansion measures as well flexibility is a complex problem, especially when considering realistic large-scale network models. To solve such problems, realistic large-scale network models have not been used yet, even though they provide very relevant benefits, as argued in Section 2.3.

This problem becomes even more complex once multiple time periods for decision-making are introduced, turning the single-stage into a multistage problem. Finally, the problem complexity expands again, once uncertainty is considered in the long-term planning problem formulated as multi-scenario multistage DNP leveraging flexibility as non-conventional expansion measure. Given that the first of these three complex problems is already poorly addressed in the literature, a sequential approach to developing models is adopted. That is, the first model will solve the single-stage DNP problem with and without flexibility as a non-conventional expansion measure; the second model developed consecutively will solve the multistage DNP problem using conventional expansion measures and flexibility; finally, a methodology for solving the multi-scenario multistage DNP problem using conventional expansion measures and flexibility is proposed.

In terms of solution methods, approaches based on mathematical programming are making steady progress and have the advantage of guaranteeing optimality when solutions are found. However, due to the complexity of the problem, these methods have yet to prove that they can deliver satisfactory results by relying on decomposition techniques and specialised problem formulations and solvers. Metaheuristics, on the other hand, have been shown to provide good solutions to complex problems, even if the optimality of the solutions found cannot be proven. Among these metaheuristics, TS has been shown to work well even for problems characterised by a large search space, although it is often used as part of a hybrid metaheuristic (Héliodore et al., 2017; Pereira et al., 2016; Navarro et al., 2009). While TS has been applied to multistage DNP (Pereira Junior et al., 2013), it has not been applied to multistage DNP in combination with flexibility from DER. Some multistage DNP approaches have considered DG installation to reduce network expansion cost (Koutsoukis et al., 2014; Pereira et al., 2016), but none has explicitly modelled and estimated the value of load flexibility.

3 Single-stage distribution network planning

This chapter considers single-stage distribution network planning with flexibility as an alternative to conventional network expansion measures. First, the problem is defined and a mathematical formulation of the problem is presented. Secondly, a methodology for single-stage distribution network planning based on the Tabu Search metaheuristic is presented as the chosen solution method. A case study is then carried out to demonstrate the capabilities of the developed model on a realistic large scale network. The case study also includes an analysis on a small feeder to illustrate the functionalities of the model. Finally, the results are presented and discussed, and conclusions are drawn. The content of this chapter has already been published in (Ziegler, Prettico, et al., 2023).

3.1 Single-stage distribution network planning with and without flexibility

As discussed in Section 1.1, the electric distribution system is undergoing a major transformation, with large numbers of new DER expected to be connected to the DN over the next few decades. This introduction of significant numbers of new DER, particularly EVCs and HPs, is expected to introduce new and increase existing peak network peak loading, for which the DN will need to be upgraded. Both new extreme peak-loads and increased existing peak-loads are expected, especially if the time synchronisation of loads cannot be prevented by a mix of techno- organisational measures such as from regulation, technological standards, grid codes, new tariff design and flexibility organised in local flexibility markets. Conventional grid expansion measures, such as transformers and lines, are characterised by high up-front costs and long asset lives. Power system flexibility is expected to deliver economic savings by helping to avoid extreme peak network loading, which requires an oversized network and therefore underutilised assets. In order to accommodate new DER and avoid the investment and operational costs associated with oversized networks, it is important not only to plan the network efficiently with conventional expansion measures, but also to consider non-conventional measures such as load flexibility provided by DR in DNP. This chapter deals with the problem of DNP with conventional expansion measures and flexibility as a non-conventional alternative measure. The proposed solution provides a straightforward financial comparison between conventional and non-conventional single-stage DNP.

3.2 Problem statement

In the following, a general formulation of the problem for a single-stage DNP is presented, using both conventional and non-conventional expansion technologies and solutions. In other words, a distribution network in the initial year is expected to experience load growth and/or DER installation by the year of the planning horizon, resulting in the need to invest in network expansion to safely accommodate the new loading situation. The single-stage DNP problem aims to identify the optimal investment decisions at the beginning of the planning horizon to meet the expected load growth and/or DER installation. The expansion measures considered in the decisions are conventional (transformers and lines) and non-conventional (flexibility contracting). Contracted flexibility assumes that a certain amount of loads can participate in DR, thus providing load flexibility by reducing their peak load contribution by a certain margin. This flexibility is assumed to be contractable by the DSO in long-term contracts and to be reliably activated to reduce the peak load of the network relevant to the planner. The resulting expansion plan must take into account all operational limits. Those limits ensure the safe operation of the DN while respecting the design limits of the primary equipment of a power system.

A general problem formulation for single-stage DNP using conventional and non-conventional expansion technologies and solutions is presented in Section 3.3.

3.3 Problem formulation

The objective function is to minimise the sum of the annuities for the investment costs and the operational costs resulting from the total network expansion required in the year of the planning horizon. The investment annuity includes the investment cost of lines and transformers discounted using the discounting factor over the expected life of the asset. The calculation of total annual costs is based on the investment annuity plus the annual maintenance costs for transformers and lines and the annual contracting costs for flexibility. Annuities of conventional expansion measures are dominated by investment cost (CAPEX), while annuities of flexibility contracting are dominated by operational and maintenance cost (OPEX). Annuities are used to make investments in assets with different expected lifetimes comparable. This ensures better comparability between conventional network expansion investments, such as power lines and transformers, which have very long lifetimes of up to 40 years, and non-conventional alternatives, such as flexibility products, which have a much shorter life cycle and a generally different cost structure. Voltage limits for each voltage level are defined by an upper and lower permissible operating voltage. Thermal limits are defined by a maximum permissible steady-state current for transformers and power lines. Full connectivity and radiality of the network is ensured when lines or transformers are added or removed. The simultaneity of consumption and generation throughout the network and over the course of a year can create different network loading situations. Due to the increasing penetration of DG in many distribution networks, reverse power flows may occur locally and need to be taken into account in planning. The load situation with the predicted maximum load of the system is the relevant one for planning and is defined as network peak. The future network at peak load is defined by the loads, generators, the upstream system supply and their consumption and generation profiles. It is based on a deterministic input describing the distribution and sizing of loads and generators throughout the network at peak. The detailed future peak load network considered in the case study is reported in Section 3.5. The future network and its loading in the planning horizon year result in constraint violations, which are removed by determining the optimal set of binary expansion decision variables for all branches (transformers and lines), as well as binary contracting decision variables for flexibility contracts existing at some network nodes. While the former decision variables represent the installation of additional or capacity expansion of existing transformers and lines, the latter represent the load reduction of contracted flexibility at the time of the network peak relevant for planning. The optimal set of decision variables results in a network candidate with the lowest total annual cost at the planning horizon, while all operational constraints are met and all loads are supplied. Distribution losses are not included in the optimisation objective, but they are relevant and are included in the calculation of voltage drops and are therefore taken into account to ensure that no constraint violations occur. Also, the value of lost load due to supply interruptions is not considered in this DNP problem as only feasible solutions are accepted.

3.3.1 Mathematical problem formulation

In the following, the OF of the problem formulated above is described mathematically.

$$\min \quad \sum_{i=1}^{n} \frac{1}{(1+r)^i}(A(G) + A(F)) \tag{3.1}$$

where

$$A(G) = A^{inv}(G) + A^{op}(G) \tag{3.2}$$

$$A(F) = A^{op}(F) \tag{3.3}$$

$$A^{inv} = C^{inv}\, \alpha_{n,r} \tag{3.4}$$

$$A^{op} = C^{op}_{li,tot} + C^{op}_{tra,tot} + C^{op}_{fl,tot} \tag{3.5}$$

$$\alpha_{n,r} = \frac{1}{1 - \frac{1}{(1+r)^n}} \tag{3.6}$$

$$C^{inv} = C^{inv}_{li,tot} + C^{inv}_{tra,tot} \tag{3.7}$$

$$C^{op}_{li,tot} = \sum_{br_{ij} \in \Omega_{pl}} \sum_{li \in \Omega_{li}} b_{br_{ij,li}}\, C^{op}_{li}\, l_{br_{ij}} \tag{3.8}$$

$$C^{op}_{tra,tot} = \sum_{br_{ij} \in \Omega_{ds}} \sum_{tra \in \Omega_{tra}} b_{br_{ij,tra}}\, C^{op}_{tra} \tag{3.9}$$

$$C^{op}_{fl,tot} = \sum_{i \in \Omega_{dr}} \sum_{fl \in \Omega_{fl}} b_{i,fl}\, C^{op}_{fl} \tag{3.10}$$

$$C^{inv}_{li,tot} = \sum_{br_{ij} \in \Omega_{pl}} \sum_{li \in \Omega_{li}} b_{br_{ij,li}}\, C^{inv}_{li}\, l_{br_{ij}} \tag{3.11}$$

$$C^{inv}_{tra,tot} = \sum_{br_{ij} \in \Omega_{ds}} \sum_{tra \in \Omega_{tra}} b_{br_{ij,tra}} \, C^{inv}_{tra} \tag{3.12}$$

Investment and operational constraints

The OF is subject to the following investment and operational constraints.

$$h(G, F) \geq 0 \tag{3.13}$$

Where h, shown in equation (3.13), is a generic function representing all investment and operational constraints. These constraints are described in the following.

An upper boundary for investments in conventional expansion is limiting the number of parallel lines per power line branch as well as the number of parallel transformers per distribution substation branch.

As the DNP problem considers the peak-load in the network as the relevant time slice for planning (Teichgraeber et al., 2022; Mateo, Gomez San Roman, et al., 2011), constraints describing operational limits of network assets have to be hold at these peak times. That means all common power flow equations must be solved and the following operational constraints be hold. The bounding constraint describing the permissible voltage at any node (3.14) and the inequality constraint describing the maximum current on any branch (3.15) are formulated.

$$V_i^{min} \geq V_i \geq V_i^{max} \quad \forall i \in \Omega_b \tag{3.14}$$

$$I_{br_{ij}} \leq I^{max}_{br_{ij}} \quad \forall ij \in \Omega_{br} \tag{3.15}$$

Additionally, full network connectivity (i.e. no unsupplied loads or network assets exist) is ensured at all times by a network connectivity constraint. This means that all nodes and consequently all loads are connected and none remains isolated. The network radiality constraint ensures that the network remains radial after new transformers and lines are added. Complying with all network operational constraints is ensured by power flow and graph analysis. As only feasible solutions are considered, the value of lost load is not part of the OF, shown in equation (3.1).

3.4 Solution method: Tabu Search

A solution methodology is proposed below to solve the single-stage DNP problem described in Section 3.3. This single-stage DNP problem aims to identify optimal investment decisions by considering conventional (power lines and transformers) and non-conventional (contracted flexibility) distribution network expansion technologies and solutions. Therefore, the DNP is transformed into an ADN planning problem.

Developing a model for the long-term planning of large-scale ADN is a challenging undertaking. In particular, the large number of decision variables and the large non-convex search space, characterised by many local optima, make the optimisation problem very difficult to solve. To overcome these limitations, the model presented in this thesis relies on a metaheuristic optimisation algorithm. This choice also means that it is easy to expand from a single-stage model to a multistage model. Among the metaheuristic search algorithms, population-based algorithms initially seem easier to implement as there are many generic template programs available, but they often require complex mechanisms to manage the solutions of the population. In general, their performance for large-scale DNP remains to be proven. The chosen solution method to find the optimal expansion decisions for the year of the planning horizon is based on the TS meta-heuristic. By combining technically and economically appropriate simple heuristics with the guiding intelligence of the TS algorithm, the TS meta-heuristic can make use of extensive expert knowledge of system behaviour. This ability to encode expert knowledge to produce technologically likely feasible candidate solutions, combined with the guided search of the TS algorithm implementation, has shown promise in tackling realistic large-scale networks (Laguna, 2018; Pirim et al., 2008). In TS, simple heuristic rules consistent with power system engineering principles and network design standards can be defined as elementary moves. This is particularly useful in DNP, as the problem is conditioned by very localised issues, that arise from varying loading of network elements. To resolve theses issues local decisions, using elementary moves, can be made relatively independent of each other, even in large-scale systems. That is, the solution method scales well with respect to the problem size. This approach helps to navigate and reduce the search space by constraining the neighbourhood solutions (or network candidates) generated during the search process.

Increasing the rate of feasible solutions among those generated during the search procedure is an important goal. This is mostly due to the fact that the search space can be truly gigantic and that each solution is individually checked for feasibility. While in mathematical programming, the constraints shown in equations (3.13) are formulated as an input to the solver, it usually works quite different in meta-heuristic approaches (Coello Coello, 2002). In the latter, various strategies to handle constraints exist. One of the methods that is comparable to the way constraints are handled in mathematical optimisation, is called constraint consistent GA (i.e. applied in Genetic Algorithms), where the search space is pruned such that the search procedure never finds an infeasible solution (Kowalczyk, 1997). While constraint-consistency in candidate generation might be possible, it seems not very promising for the problem at hand, as least if the solution method should keep some general applicability. Arguably, the most prominent among the methods to handle constraints in meta-heuristic optimisation is the use of penalty functions, which weight the violations of constraints into the objective function using various weighting techniques. In order to evaluate those weights, the violations need to be identified, which in distribution system planning is usually achieved by some variant of power flow calculations (Arasteh et al., 2016; Haesen et al., 2009; Saboori et al., 2015; Zeng et al., 2016). While the integration of the power flow runs in the metaheuristic algorithm depends on the specific algorithm and its implementation, it is commonly run to check the constraint violations of new candidate solutions. In the case of the TS implementation in this thesis, in each iteration, power flows are run consecutively for each candidate solution until a feasible candidate is identified. In the case of meta-heuristics, it is possible to carry out the power flow calculations, using directly existing, standard, and already optimised power flow tools (like pandapower (Thurner et al., 2018)), which takes only 50 milliseconds in the large-scale realistic networks of this paper's case study (on an intel core i7, dual core @ 1.8 GHz, 4 GB RAM).

The classic TS algorithm is a deterministic local search strategy with memory and was originally presented by (Glover, 1986). Probabilistic elements can be added to the deterministic local search. Obviously, in highly combinatorial problems such as distribution system planning, such search strategies lead to locally optimal solutions. To escape these local optima, diversification and intensification strategies are used in combination with memory capabilities for efficient search space navigation. Memory capabilities are usually divided into a short-term memory and a long-term memory. Short-term memory, also called recency-based memory, stores previously visited candidates for a certain number of iterations (tabu tenure). Long-term memory, often implemented as frequency-based memory, supports adaptation intensification and diversification in more difficult optimisation problems. Traditional search strategies with so-called explicit memory store complete candidate solutions during the search process, which would require an infeasible amount of memory. To significantly reduce this memory requirement, search strategies with attributive memory are commonly used in TS. In such TS memory structures attributes of moves are stored instead of complete solutions (Laguna, 2018). In addition to the TS terminology describe so far, other relevant terms that are used throughout this thesis are defined in Appendix A.1.

3.4.1 Algorithm overview

An overview of the developed TS algorithm is given below and shown in Figure 3.1.

In general, unlike other meta-heuristic optimisation algorithms that start with random initial candidates, the TS procedure starts with an initial solution that is feasible but may be far from the optimum. This provides an advantage in terms of computational efficiency, as an oversized network can be easily acquired before starting the TS.

This is because the theoretical or unconstrained search space contains few feasible solutions, which would most likely result in a high computational cost to find the first feasible solution from which the TS algorithm can work efficiently. Starting from the feasible initial solution, a set of likely neighbourhood solution candidates is generated. The objective function value of each candidate solution is then calculated. The list of candidate solutions is sorted by OF value and starting from the candidate with the best value, feasibility is checked by power flow analysis and connectivity checks. This process is repeated until the first feasible candidate is found. The current best solution and the tabu list are then updated accordingly. The update of the tabu list includes the tabu activation for moves leading to the newly accepted current best solution as well as the deactivation of tabu active moves based on the tabu tenure criteria. Finally, if the termination criterion is not met, the process is started again with the generation of a new set of candidate solutions based on the neighbourhood of the newly assigned current best solution.

In the following, the production of the initial solution with a simple heuristic as well as the meta-heuristic TS implementation are described in more detail.

3.4.2 Heuristic solution

The simple heuristic solution (HS) algorithm produces the initial solution (network) to be used as the starting point in the TS algorithm. As mentioned above, this initial solution represents a feasible network expanded to cover the load situation resulting from the future scenario. This initial solution provided by the HS algorithm represents a feasible network that is not optimised

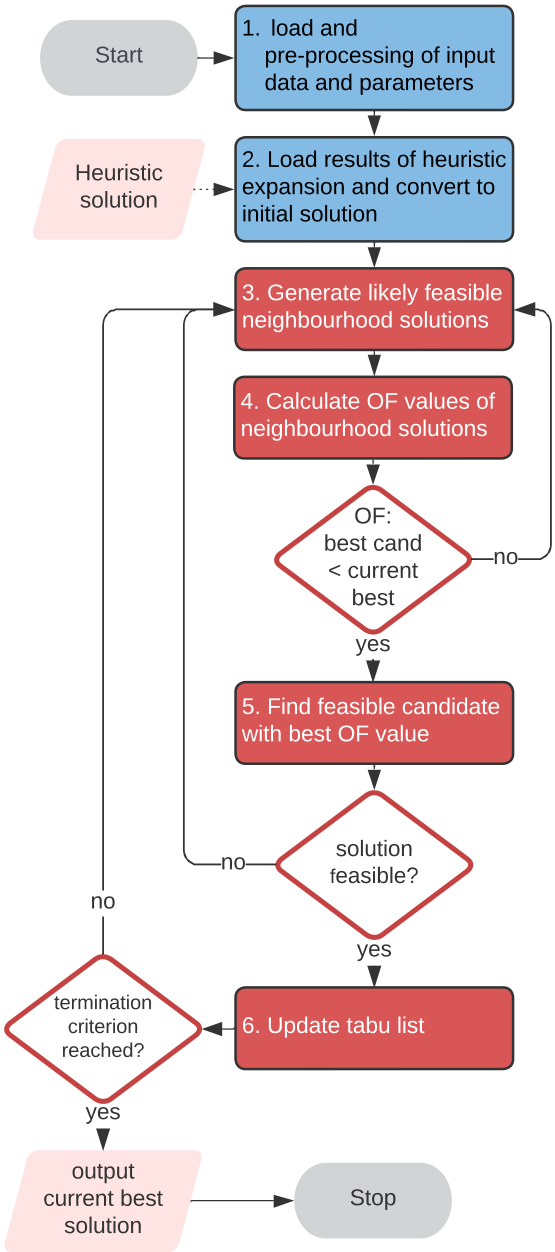


Figure 3.1: TS algorithm flowchart

for cost or any other objective. In the following, the simple heuristic algorithm that produces the initial solution is described. The necessary input data and parameters are also described.

First, a preprocessing is performed based on the analysed scenario, as shown in Figure 3.2. The RNM files are parsed into a georeferenced Pandapower network. Operational and planning parameters are defined. The resulting network is populated with loads and generators according to the input scenario. Such a network, here called *network 2030*, is not feasible as it suffers from constraint violations due to the newly added loads and generators. This network is then passed to the HS algorithm, shown in Figure 3.3, which expands its transformer and line capacity until there are no more constraint violations. Finally, the feasible network is obtained, referred to here as the *expanded network HS solution*. Note that the heuristic solution produced by this HS algorithm is not optimal and is likely to be oversized. However, it is a feasible solution and the starting point from which the TS algorithm begins its optimisation search.

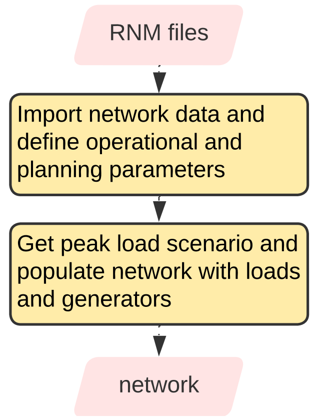


Figure 3.2: Pre-processing for HS

3.4.3 Tabu Search implementation

The following Section presents the TS codification, which is the descriptive implementation of the TS algorithm. The most important general TS terms used in the following implementation of the TS algorithm are listed in the Appendix A.1.

Tabu Search codification

The TS implementation is based on the following codification.

Search strategy: The search strategy used in this thesis is a variation of steepest search and best-improving search. This means that, like the best-improving search, negative move values are allowed, but they are limited by a margin that is set to 10.

Candidate list strategy: In this TS implementation the first improving strategy is used as a candidate list strategy. That is, different moves are inserted to produce a list of likely feasible candidates for which the move values can be efficiently computed. The move value describes how a move, or a set of moves in the case of simultaneous insertion, affects the OF value, positively or negatively. This list is then sorted by move value and the feasibility of the candidates is calculated, starting with the best-valued candidate. The best valued candidate should have a positive move value, but can also be the candidate with the least negative move value if there is no positive valued move in a given iteration. The feasibility check includes a full network connectivity and radiality check, as well as the execution of a power flow algorithm that must converge while satisfying all operational constraints.

Moves: TS moves are defined as functions describing modifications to the current best network candidate. In this model, the modifications can be the removal, replacement or parallel addition of a transformer or line and the contracting of a flexibility resource at a given node of the network, as well as the removal of the latter. The moves for conventional network expansion used in this thesis are listed in Appendix A.2. There, the moves for transformer expansion are shown in Table A.1, for line expansion are shown in Table A.2 and for non-conventional grid expansion based on flexibility contracting are shown in Table A.3.

Neighbourhood structure: The neighbourhood structure describes how the neighbourhood of the current best solution is created. In the underlying model of this work, the set of moves applicable to create the neighbourhood in one iteration depends on the currently tabu-active elements in the tabu list as well as an input parameter that limits the maximum size of the neighbourhood. A number of moves are made in parallel in order to produce a set of candidates of the size of the neighbourhood.

Size of the neighbourhood: The neighbourhood size is set to a maximum of 300.

Insertions of moves: Creating neighbourhood solutions by randomly inserting moves is not very promising, considering the computational effort required. Therefore, targeted insertions at specific network elements have been implemented. Thus, move insertions are strategically made directly at network elements that are prone to constraint violations or in their electro-physical proximity.

Insertion complexity: Here, move insertions are simple swaps of moves based on initial insertions registered in the TS vector, as well as potential violations in the current best candidate. These move variations describe a set of possible changes that can be applied to the edges and nodes based on their previously registered value in the respective TS vector. Furthermore, ejection chains are implemented that create a single candidate by combining the downgrading of an existing line or transformer expansion with the contracting of flexibility in the affected segments of the network. The moves and ejection chains used in this thesis are listed in Appendix A.2.

Tabu search vector: Each TS vector is a description of a network candidate as a set of moves which have been applied with respect to the original network. An example TS vector (bottom row) of a candidate network is shown in Table 3.1. The top row indicates the distinction between edge and node type network locations, and the middle row indicates the index and element type at the edge or node (conductor and transformer for edges and flexibility for nodes). The size of the TS vector is equal to the sum of the total number of lines and transformer edges in the network. A second TS vector for network nodes exists, which in this thesis encodes the application of load flexibility to the network nodes. The TS vectors of the original network contain only zeros, while the TS vector of the initial heuristic solution contains the integers describing the moves, which encode the non-optimal initial expansion performed on the respective edges in the network. As the heuristic-based initial solution does not model flexibility contracting as alternative expansion measure, the TS vector encoding flexibility is zero for each node. A candidate solution's TS vector contains the integers of the moves encoding the change inserted at a given edge or node index with respect to the original network.

Edges										Nodes				
pl_1	pl_2	pl_3	$\cdots$	pl_n	ds_1	ds_2	ds_3	$\cdots$	ds_m	dr_1	dr_2	dr_3	$\cdots$	dr_p
0	3	1	...	0	8	0	4	$\cdots$	2	0	1	3	$\cdots$	1

Table 3.1: Illustration of a TS vector with n power line edges (pl), m distribution substation edges (ds) and p DR nodes (dr)

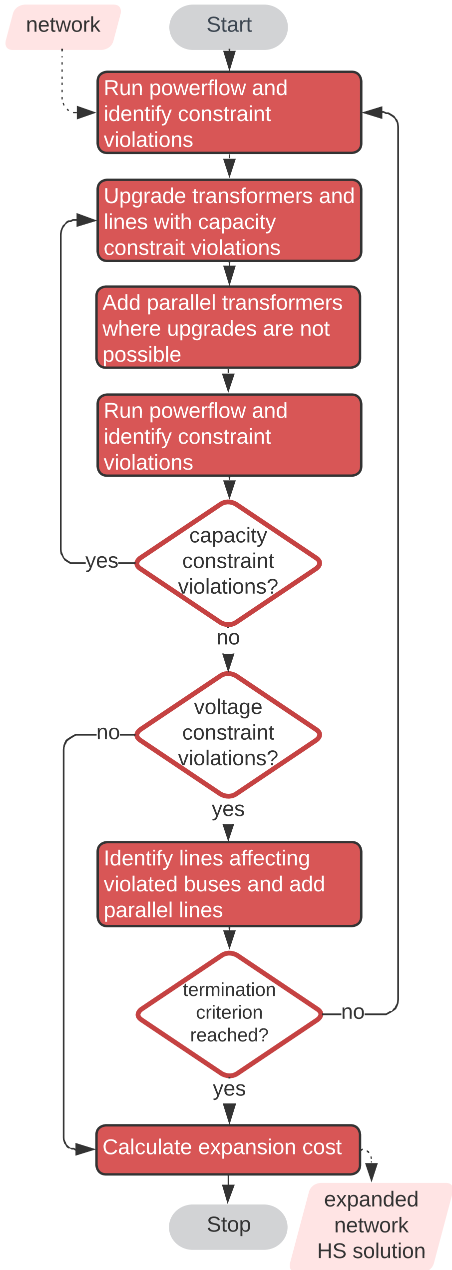


Figure 3.3: HS algorithm flowchart

3.5 Case study

In this section, a set of case studies analyse the impact of projected investment cost, combining conventional network expansion and non-conventional flexibility solutions.

3.5.1 General modelling assumptions

The general modelling assumptions relevant to this case study are described below.

The network operational constraints are parameterised as follows. The voltage constraint for the MV and LV network levels is set to +/-10 % of the nominal voltage. The power capacity constraint for lines is set to 100 % and for transformers to 90 % of their respective nameplate capacities.

The economic assumptions regarding the investment of assets are parameterised as follows. The discount rate for the remuneration of assets is based on the weighted average cost of capital (WACC). This discount rate is set at 6 %. The regulatory expected lifetime of 40 years for transformers, lines and cables is based on the Spanish regulation (Comisión Nacional de los Mercados y la Competencia, 2019). The planning horizon is set to ten years. Investment and maintenance costs for conventional network expansion assets are based on Official State Gazette No. 297 (Ministerio de Industria, Energía y Turismo, 2015). The economic assumptions regarding the provision of flexibility are formulated as an estimated annual capacity price for the contracted flexibility, which indirectly includes the cost of the energy used to provide the flexibility service. A possible price range for flexibility contracts found in the literature is between 50 and 140,000 €/MW per year, derived from various sources of cost information on the electricity system in Spain (Linares and Rey, 2013), the Spanish electricity market operator (OMIE, 2019; OMIE, 2021), as well as the relevant sources from the operation of the flexibility market in the UK (UKPN, 2021; SP Energy Networks, 2022). Inspired by this literature review and tested with the planning model, a range of annual flexibility costs from 0 to 5,000 €/MW is used in the sensitivity analysis in Section 3.6.1. The cost of flexibility contracts used for the large case in Section 3.6.2 is based on the result of the literature review as well as the sensitivity analysis.

For the heuristic search procedure, the minimum additional capacity margin of new transformers is set to 40 %; the limit on the maximum number of parallel lines to be added is set to 4; the maximum number of parallel transformers after expansion is set to two and four for the MV and LV levels, respectively.

The peak load hour relevant for expansion planning is based on the load curve dataset of the Spanish transmission system operator REE (RED ELÉCTRICA DE ESPAÑA, 2020). The peak load is then scaled with respect to the total installed load of the case study in the Albacete network.

3.5.2 Load scenarios and initial solution

The initial solution is based on the simple heuristic described in 3.4.2, and used as a starting point for the TS algorithm. The two load scenarios considered (2020 and 2030) and results are described below.

Albacete 2020

The network model shown in 3.4 covers about one third of the urban area of the city of Albacete in the autonomous region of Castilla-La Mancha, Spain, with a total population of about 165,000 living in an area of about four by four kilometres. This open source network model (CC BY-SA 4.0) is publicly available for download (Mateo, 2022).

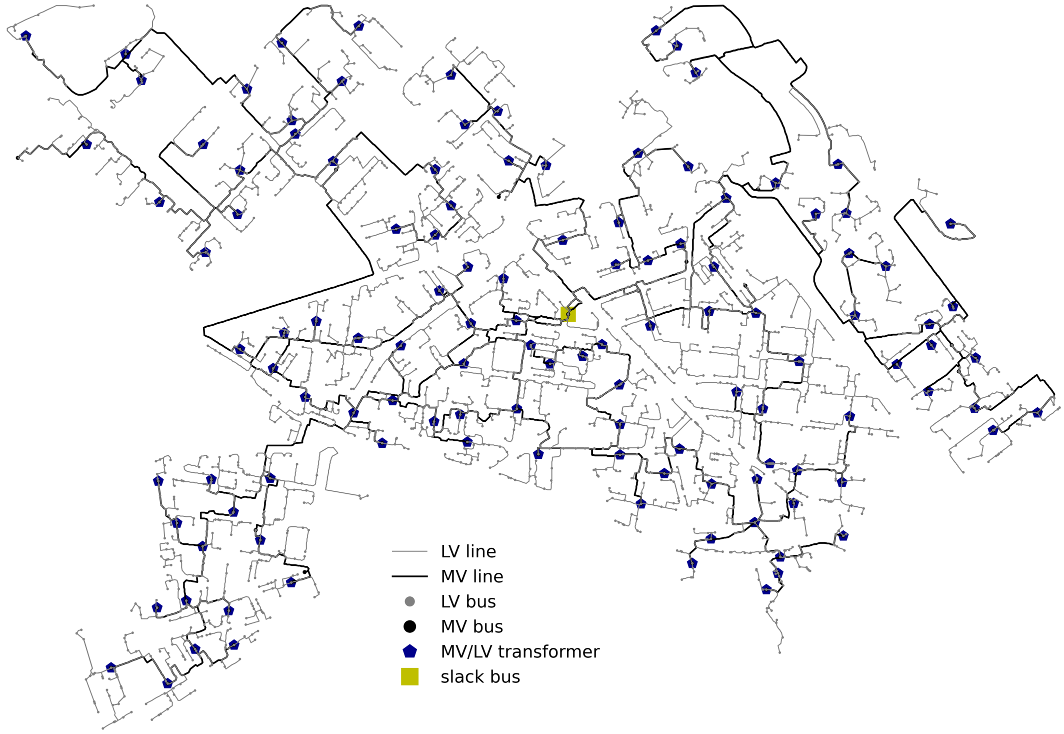


Figure 3.4: Network model of district of Albacete

The network shown is a subset of the full Albacete network, which was built using the Greenfield RNM (Mateo, Prettico, et al., 2018; Mateo, Gomez San Roman, et al., 2011). At the beginning of the planning period, in 2020, the network includes two voltage levels, namely 20 kV (with 134 buses and 32 km of power lines) and 0.4 kV (with 2628 buses and 66.55 km of length). There are 121 MV/LV distribution transformers installed with a total nameplate capacity of 61.5 MVA. There are 2507 LV loads totalling 40.24 MW and 12.07 Mvar and 12 MV loads totalling 35.59 MW and 10.68 Mvar. Peak hour power consumption is the relevant time slice for expansion planning and is estimated using simultaneity factors applied to individual load peaks as described in (Mateo, Gomez San Roman, et al., 2011).

Albacete 2030

Based on load growth assumptions considered in this case study, the Albacete district system introduced in the previous Section undergoes a significant load growth due to substantial installation of EVCs until the year 2030. Based on the Eurelectric scenario with a high EV penetration, four million EV are expected to be operational in Spain by 2030 (*Connecting the dots: Distribution grid investment to power the energy transition* 2021). This translates to 11,335 EVCs with a total installed capacity of 47.77 MW for Albacete and 3,575 EVCs with 14.9 MW for the district modelled in this case study. Following the EVC classification contained in IEC 61851 (IEC - TC 69, 2017), the charging power is allocated to 93.5 % of the chargers (39.19 MW) assumed to be slow chargers with a power rating of 3.7 kW each, 6.2 % (7.77 MW) to be quick chargers with 11 kW each and 0.3 % (0.8 MW) to be fast chargers with 22 kW rated power each. These are normally distributed over the city and installed on LV buses only. The total EV load active in the network represents 25 % of the total expected charging capacity, which is the peak-load contribution expected in the Eurelectric scenario (*Connecting the dots: Distribution grid investment to power the energy transition* 2021).

For this network model, it is assumed that all EV quick, rated at 11kW, and fast chargers, rated at 22 kW, are capable to participate in DR by reducing their load to 50 % of their contracted power at peak hour (IEC - TC 69, 2017). Furthermore, 392 pre-existing loads with sum of 12.53 MW provide flexibility similar to the EVC, reducing their load to 50 % and providing a total load reduction potential of 6.26 MW. This results in a total DR potential of 7.67 MW.

3.5.3 Albacete Feeder network

To illustrate the conventional and non-conventional expansion optimised by the developed TS algorithm, a small MV/LV feeder from the north-eastern corner of the Albacete district, described in Section 3.5, is presented below. The MV feeder with five MV/LV distribution transformers and their respective LV feeders are isolated from the original network (section 3.5.2). This feeder contains two voltage levels, namely 20 kV with five buses and 1.196 km of power lines and 0.4 kV with 91 buses and 2.718 km of length. The five MV/LV transformers have a total nameplate capacity of 2.45 MVA. The loads consist of 222 LV loads totalling 2.53 MW and 0.57 Mvar. In this case study, several analyses are carried out to understand the functioning and consistency of the solutions obtained by the TS algorithm based on the presented MV/LV feeder.

3.6 Results and discussion

In the following, the results for the feeder-type network as well as the realistic large-scale network are presented and discussed.

Firstly, the feeder-type cases are presented. In Section 3.6.1, the initial solution produced by the HS algorithm is presented. Secondly, solutions optimised by the TS algorithm are shown, both with and without non-conventional expansion using flexibility contracting. Next, in Section 3.6.1 a comparison is made between two levels of flexible load contracting potential under a reduced load growth scenario. While in one case, and the base scenario in this chapter, the load reduction of activated flexibility contracts is reduced to 70 % of the installed load capacity, in the other case the load reduction of activated flexibility contracts is reduced to 0 %, effectively shutting down the entire flexible load. Finally, the results of a sensitivity analysis are presented in Section 3.6.1, to show how sensitive the use of flexibility as an expansion measure is to the price of flexibility. This sensitivity analysis is carried out for a large number of flexibility cost values, but only a small selection of the corresponding results are presented and discussed below. In addition, to further test the results found, the sensitivity analysis is performed for two scenarios where the load reduction of activated flexibility contracts is varied, with a reduction to 0 % and to 70 % of the installed load capacity. Finally, in Section 3.6.2 the results for the realistic large-scale network are presented and discussed, for the cases with only conventional network expansion measures and the case with conventional as well as flexibility as non-conventional expansion alternative.

3.6.1 Feeder-type network

Standard scenario with and without flexibility

The initial solution, based on the simple HS algorithm described in Section 3.4.2, includes five transformer expansions with a total of 1.47 MVA additional nameplate capacity and eleven parallel line expansions with an additional 0.250 km in length. As can be seen in Figure 3.5, all the transformers are extended, from the one directly on the slack bus (shown as a yellow square) to the one at the end of the MV feeder. The expanded LV line segments appear in all LV networks below the expanded transformers. This results in a total annuity of 16,664.37 € for the MV/LV feeder for the initial solution produced by the simple heuristic.

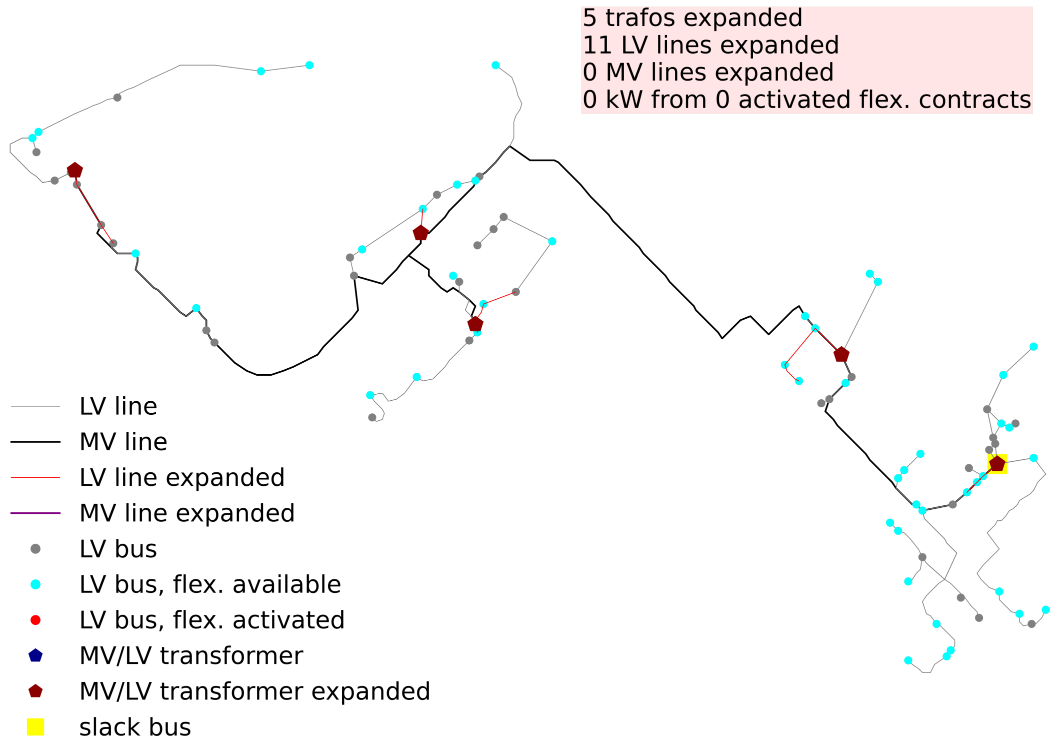


Figure 3.5: Feeder case studies, heuristic solution

Running the TS algorithm on the initial solution presented in the previous paragraph produces an optimised solution as shown in Figure 3.6. This solution includes five transformer expansions with a total additional nameplate capacity of 1.24 MVA and eight parallel line expansions with an additional length of 210 m. Compared to the original solution, three parallel line expansions totalling 0.040 km have been removed and one transformer expansion has been downgraded from

630 kVA to 400 kVA. At 16,534.89 €, the total annuity for the MV/LV feeder expansion is 2.16 % lower than the initial solution presented in the previous case. This is achieved by avoiding the expansion of three LV lines.

In this case, the use of flexibility contracting is introduced as an alternative to conventional expansion, assuming the 2030 scenario as described in Section 3.5.2. The price considered for flexibility is 5000 €/MW and year. Compared to the initial solution, this results in a network expansion with five transformers and an additional nameplate capacity of 1.24 MVA, as in the previous case. The expansion of the power lines results in six LV power lines with a total length of 0.180 km, instead of eight power lines with a total length of 0.210 km in the previous case. In addition, four flexibility contracts are activated, with a total load reduction of 11.6 kW, as shown in Figure 3.7. The resulting expansion annuity is 16,420.62 €, which is 0.7 % less than the conventional expansion-only solution presented in the previous case. It can be seen that in this scenario no significant reduction in total annuity is achieved, as the available flexibility does not provide sufficient load reduction to allow less transformer expansion than in the previous case.

Scenario with reduced load including flexibility

In the case of reduced load growth, loads are scaled to lower levels than in the 2030 baseline scenario described in Section 3.5.2. The reduced peak load consequently results in the removal of all but two transformers and one transmission line expansion from the initial solution. As expected, a greater reduction in expansion measures is obtained, as the initial solution is based on the peak load of the 2030 scenario and the oversized expansion, as shown in the first two cases. No flexibility contracts are activated, as shown in Figure 3.8. The resulting expansion annuity is 6,322.11 €, which, not surprisingly, is significantly lower than in the 2030 load growth scenario. This confirms the sensitivity of the planning algorithms to the future load in the year in which the expansion is planned.

In the previous case, the contracted flexible loads are reduced to 70 % of their power consumption. The following case assumes the same as the previous scenario, but allows the flexible loads to be reduced to 0 % in the event of flexibility contracts being activated. As can be seen in Figure 3.9, this results in the removal of all but one transformer and the removal of all power line expansions from the initial solution. In addition, seven flexibility contracts are activated, resulting in a load reduction of 54.03 kW. It can clearly be seen that, compared to the previous case, the second to last transformer in the MV feeder is not expanded, but some of the flexibility downstream of the transformer is activated. Similarly, it can be seen that in this case the line expansion present in the previous case is removed, while some flexibility is activated downstream of this line. This illustrates well how flexibility, if sufficiently available, can work as an alternative to the conventional power line expansion selected by the TS algorithm through the use of ejection chains, as described in Section 3.4.3. The total annuity of 3,221.12 € is therefore unsurprisingly low. Despite representing this extreme case, these results highlight the importance of the amount of flexibility that can be made available for each load, which is a critical factor for flexibility to serve as an alternative to conventional reinforcement.

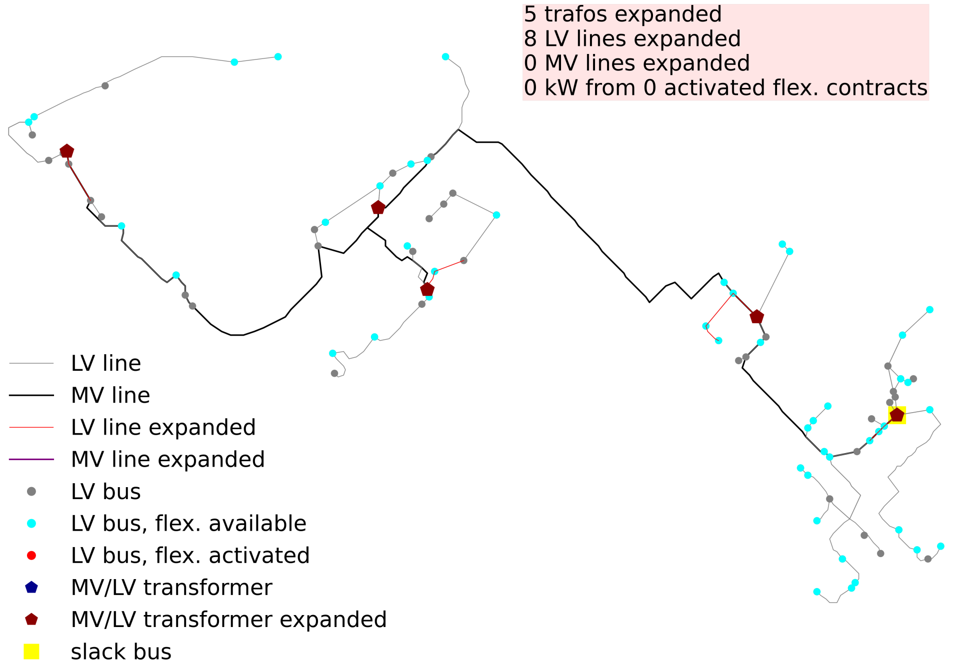


Figure 3.6: Feeder expansion plot without flexibility activation

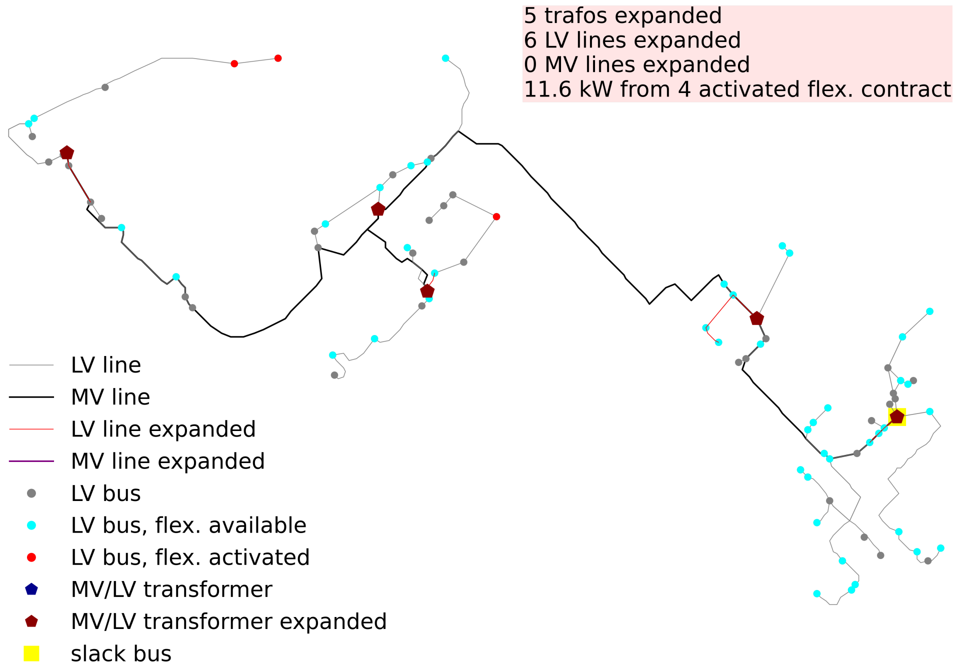


Figure 3.7: Feeder expansion plot with flexibility activation

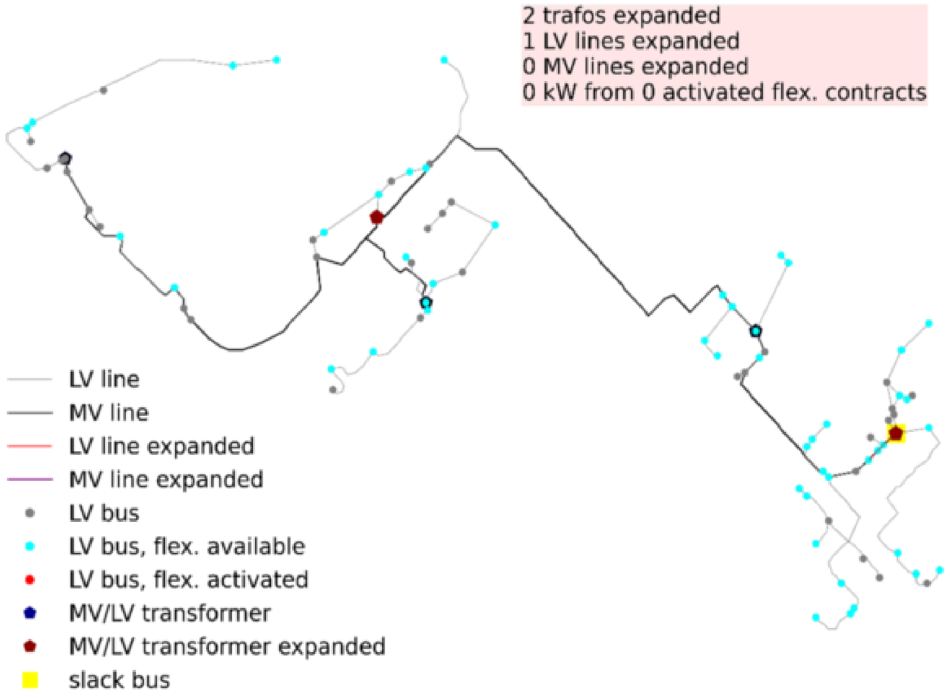


Figure 3.8: Feeder expansion plot with reduced load and 30 % flexibility potential

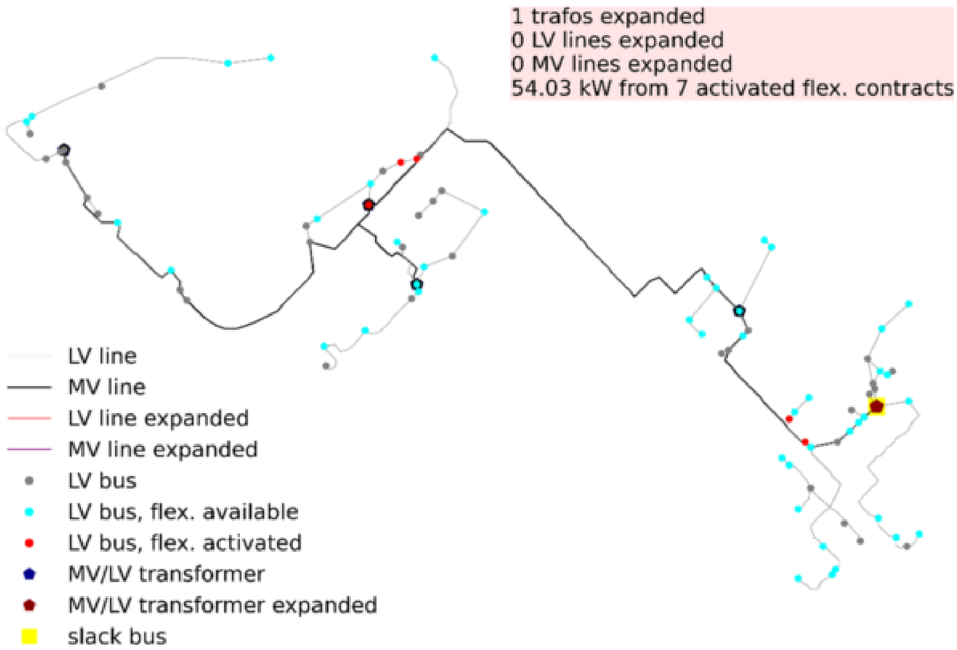


Figure 3.9: Feeder expansion plot with reduced load and 100 % flexibility potential

Scenarios with sensitivity to flexibility cost

In order to determine the sensitivity of the ADN planning methodology to the cost of flexibility, a brief sensitivity analysis is carried out. As in the previous section, two levels of load reduction are examined in the case of flexibility contract activation. In the more conservative case, the active power consumption of the flexible loads is reduced to 70 % of their peak load contribution. In other words, 30 % of the nominal active power of the load is available as flexibility. In the more extreme case, this reduction reaches 0 %, which is practically equivalent to the deactivation of the loads in question. In other words, 100 % of the nominal active power of the load is available as flexibility. The sensitivity analysis was carried out by running the TS optimisation for a wide range of flexibility costs, from 0 to 5,000 €/MW per year. It should be noted that the values on the horizontal axis are not on a linear scale, but are skewed around some of the flexibility cost thresholds. The results of this analysis, for both levels of load reduction, are shown in Figure 3.10. It can be seen that the more extreme level of load reduction leads to a significantly higher proportion of flexibility contracts being activated, here up to 27 %, as long as the cost of flexibility remains below around 860 €/MW per year. This is due to the fact that the higher total load reduction in the respective network segments allows flexibility contracting to serve as an effective alternative to non-conventional expansion measures such as power line or transformer expansion.

For the more extreme load reduction case, it shows that below an annual cost of 150 €/MW per year, the cost does not limit the use of flexibility as an alternative to conventional expansion. For a more conservative load reduction, however, it shows that this threshold is 860 €/MW per year.

The results of all the case studies presented in sections 3.6.1, 3.6.1 and 3.6.1 serve to illustrate the basic behaviour of the planning method, reducing the network expansion cost from the initial solution to the minimum while serving the peak-load and satisfying the technical constraints. Both for the case with conventional and non-conventional (flexibility) expansion measures. In addition, the different load reduction potentials for activated flexibility contracts in Section 3.6.1, demonstrates that flexibility can work well as an alternative to conventional grid expansion, if it is available in sufficient capacity at the relevant locations of the network. The last case study in Section 3.6.1 exemplifies the impact of different cost for flexibility contracting on the application of flexibility as an alternative to conventional expansion. Furthermore, the more complex injection of moves in the form of ejection chains, with flexibility contracting as an alternative to transformer expansion, is observable.

3.6.2 Realistic large-scale network

In the first case, there is no flexibility to contract, but the TS algorithm searches for candidate networks with a better objective function value that satisfies all constraints. The resulting network is shown in 3.11. The expansion requirements for conventional expansion are shown in 3.2, with a total annual cost of 282,609.18 € for a load growth of 19.78 % between 2020 and 2030. The evolution of the objective function value during the TS optimisation search procedure is shown in Figure 3.13. The load and asset data between this case and the one in the next paragraph are compared in Table 3.3.

[a] at 5000 €/MW per year

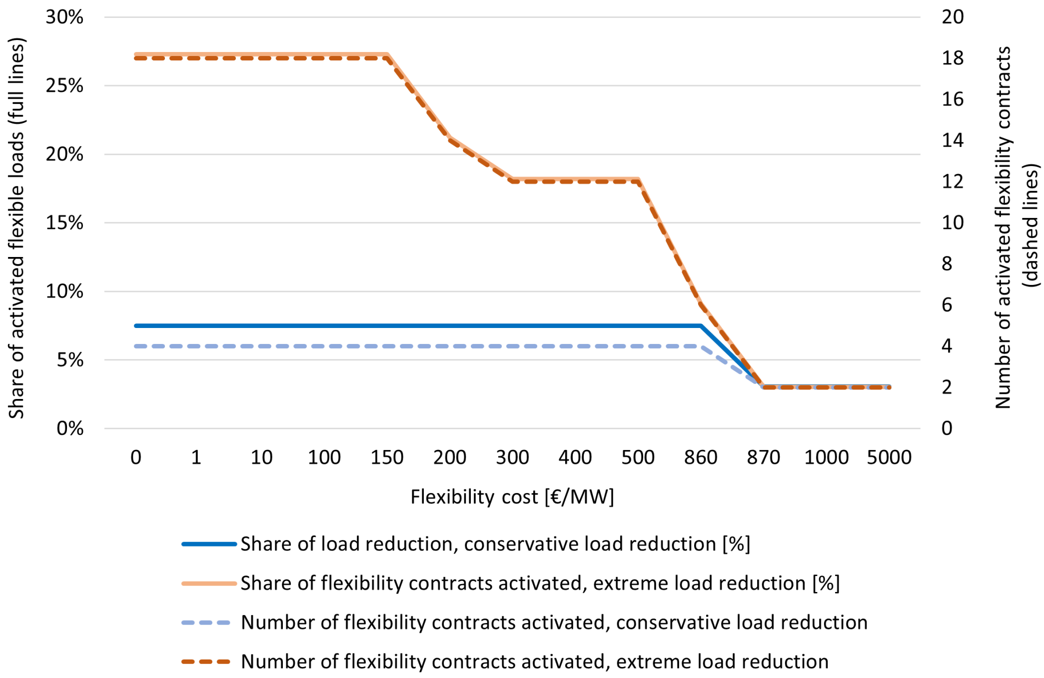


Figure 3.10: Feeder case studies, flexibility cost sensitivity analysis

	2030	2030 + DR[a]
Total annuity:	282,609.18	261,419.62
of which:		
Transformers	222,115.60	201,417.26
Power lines	60,493.59	56,910.99
Flexibility	0	3,091.38

Table 3.2: NPV of total expansion cost [€] with and without flexibility contracting.

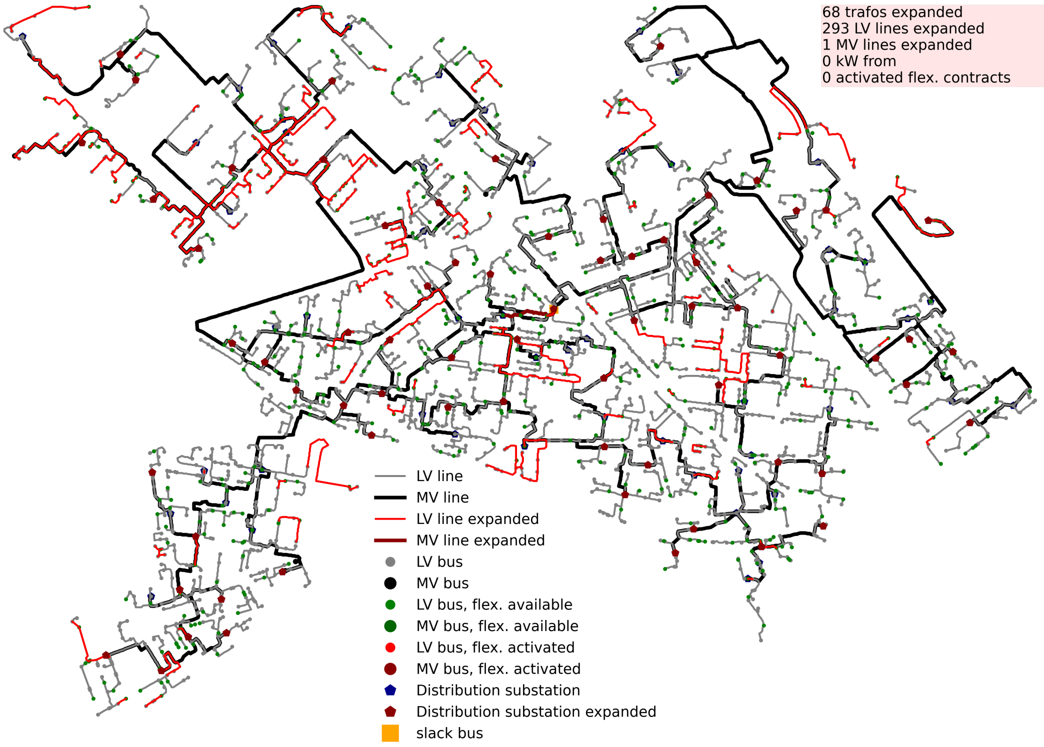


Figure 3.11: Network expansion plot without flexibility contracting

	2020	2030	2030+DR[a]
Loading			
$P_{load,tot}$ [MW]	75.83	90.83	90.21
$Q_{load,tot}$ [Mvar]	22.78	22.75	22.62
P_{losses} [MW]	1.59	2.23	2.21
P_{losses} [%]	2.10	2.46	2.45
Transformers			
MV/LV count	121	129	129
MV/LV capacity [MVA]	61.50	78.99	76.38
Power lines			
MV power lines [km]	32.01	32.17	32.17
LV power lines [km]	66.55	82.00	81.08

Table 3.3: Results of single-stage planning with and without flexibility contracting

In the second case, flexibility contracting is available as an alternative expansion measure. Based on some values from real applications of flexibility in distribution networks (UKPN, 2021; SP Energy Networks, 2022), a value of 5,000 €/MW per year was chosen for this case study on the realistic large-scale network. This results in the activation of 87 flexibility contracts on 78 buses, reducing the peak load contribution of these loads by 50 %, for a total load reduction of 618.27 kW. At 5,000 €/MW and year for flexibility contracting, this results in savings of 21,189.56 € or 7.5 % compared to the annual cost of conventional expansion alone. The expansion required for conventional expansion with peak relief by contracting flexibility is shown in Table 3.2, with a total annual cost of 261,419.62 €. As shown in Table 3.3, these savings are mainly due to a reduction of 2.61 MVA in transformer capacity and a reduction of 0.920 km in the length of the extended low voltage lines compared to the conventional expansion only case. The network after expansion with conventional and flexibility measures is shown in 3.12. The evolution of the objective function value during the search procedure of the TS optimisation is shown in Figure 3.14. Table 3.3 compares the load and asset data between the cases with and without flexibility contracting, as shown above.

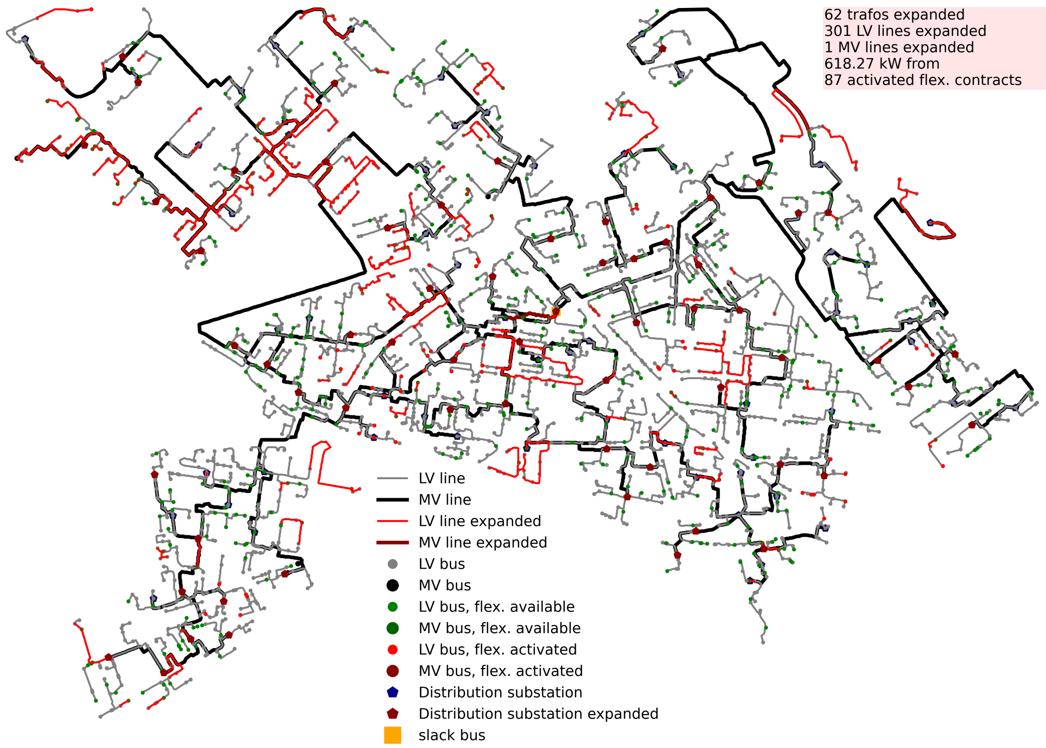


Figure 3.12: Network expansion plot with flexibility contracting

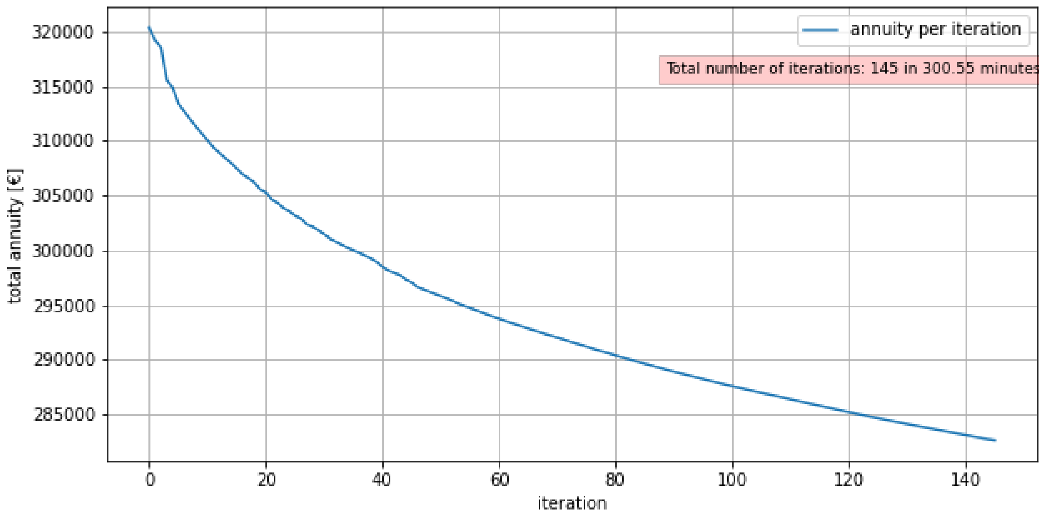


Figure 3.13: Total annuity of selected candidate solutions during the search procedure, without flexibility contracting

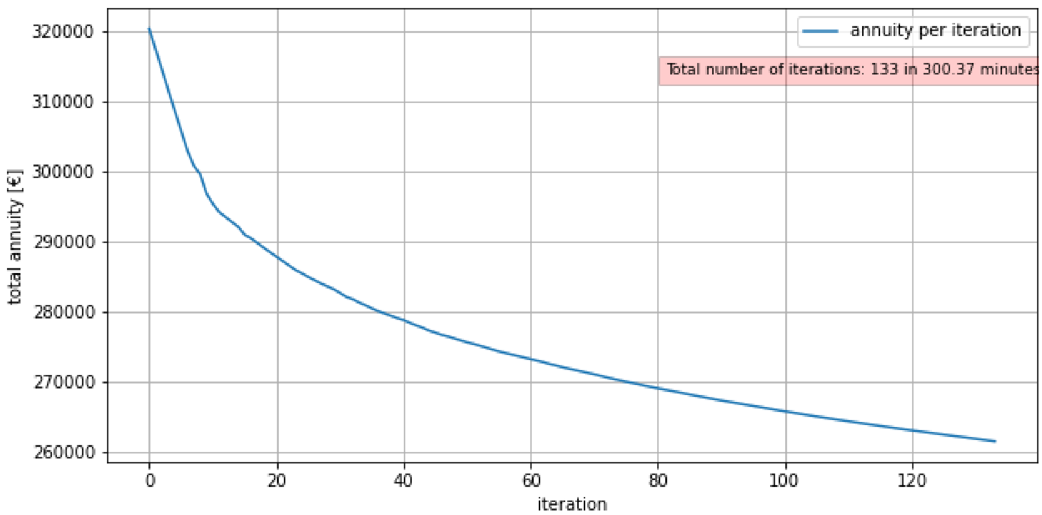


Figure 3.14: Total annuity of selected candidate solutions during the search procedure, with flexibility contracting

3.6.3 Future challenges and research

These results, based on the DNP methodology introduced in Section 3.4, show the potential for contracting flexibility to reduce the peak hour load critical to the planning problem. For further research, illustrative challenges will be presented, such as how to exploit the potential flexibility offered by larger EV charging stations in car parks or commercial buildings at the MV level, or decarbonised heating systems such as HPs. While it was shown that flexibility contracts can significantly reduce conventional network investments for capacity expansion, it remains to be seen how reliable the provision of flexibility at the peak-load can be assumed. Compared to flexibility contracts, conventional network expansion measures are characterised by high up-front investment costs, but once installed, the equipment provides the capacity continuously and reliably. In general, two approaches are taken to rely on flexibility. Explicit flexibility through flexibility contracts, where the supplier is obliged to fulfil the contract, and implicit flexibility, which relies on dynamic network tariffs that are high enough at peak times to provide an incentive to reduce load. In the case of implicit flexibility, the implementation of load reduction depends on the socio-economic preferences of consumers, which cannot be ensured deterministically. In the case of explicit flexibility provision, suppliers' compliance with the contracted flexibility is ensured by financial rewards and penalties in case of non-compliance with the response to the control signal sent by the DSO. A relevant paper gives an overview of flexibility products, markets and the various related interactions between stakeholders are presented (Villar et al., 2018). With a cost of flexibility of 5,000 or 5 €/kW and year, the economic incentive to provide flexibility seems too low to sufficiently mobilise DR participants. This is particularly so as these costs must not only encourage consumers to change their behaviour, but also cover the costs of installing and maintaining the ICT and operating the aggregator service.

Further research is needed to assess the impact on expansion costs of different DERs (heat pumps, PV, storage, etc.) at different scales deployed in the network. In addition, the impact of more smart grid technologies, such as distribution transformers with on-load tap changers, dynamic network reconfiguration through switching or dynamic line rating, on expansion costs should be evaluated. The TS optimisation method can be improved by introducing more specific and targeted move insertions to generate a higher rate of feasible and high quality candidates per iteration.

3.7 Conclusion

This chapter demonstrates the effectiveness of Tabu Search in solving the distribution network planning problem using load flexibility as an alternative to conventional network reinforcement. The approach of first generating a technically feasible but non-cost-optimal solution using a rather simple heuristic method, which is subsequently optimised by the TS algorithm, has proved successful. In addition, the use of ejection chains, as they are known in the TS literature, is shown to be useful for exchanging non-conventional with conventional expansion measures. The use of TS as a metaheuristic optimisation algorithm, whose implementation allows relatively much freedom to implement very domain-specific technical and regulatory characteristics and planning requirements, allows us to deal well even with large networks on a city scale with 2762 buses. A sensitivity analysis of the cost of flexibility contracting has shown that, depending on the particular feeder conditions and the available load flexibility, there are different thresholds below which flexibility contracting is preferred to conventional expansion in discrete steps. This work shows that the use of load flexibility as an alternative to conventional expansion can reduce total costs by 7.5 % compared to the conventional expansion solution for the large case study analysed, at a load flexibility cost of 5,000 €/MW and year. Given the high cost of distribution system expansion for the underlying load growth scenario, this would translate into significant savings if applied to the entire distribution systems of a country or region. With regard to single-stage planning, some recommendations for further research include analysing the impact of a range of relevant energy system scenarios, modelling smart grid technologies and improving the performance of the tabu search algorithm.

4 Multistage distribution network planning

This chapter considers multistage distribution network planning with flexibility as an alternative to conventional network expansion measures. Extending the single-stage DNP problem of the previous chapter, the multistage DNP problem is defined and a mathematical formulation of the problem is presented. Secondly, a methodology for multistage distribution network planning based on the pseudo-dynamic forward fill-in method and the model presented in the previous chapter is introduced. A case study is then conducted as a demonstration of the capabilities of the model being developed. Finally, there is a presentation and discussion of the results and conclusions are drawn. The content of this chapter is currently under peer-review in an impact journal, though a working paper is available (Ziegler, Mateo, et al., 2023).

4.1 Multistage distribution network planning with and without flexibility

The expected load growth due to DER penetration does not only raise the question of how much and where to invest in distribution network expansion, but also when to invest in such. This is particularly important as conventional network expansion measures (i.e. transformers and lines) are characterised by high upfront cost and long asset lifetime. In the previous chapter, the goal of the planner to prevent over-investing in network assets was treated. Consequently, another goal for the planner can be described as preventing to invest in network expansion too early. This is especially relevant due to the time value of money which described how future cost are usually considered lesser than today's cost. Postponing network investment until these are actually needed, which is commonly referred to as network investment deferral, can therefore create significant economic savings. The results presented in the previous chapter have already shown that flexibility can reduce overall network expansion cost in single-stage DNP. In this chapter the value of network investment deferral and the role of flexibility in such is explored. In the following the multistage problem will be considered over two stages. Presenting the DNP problem in two-stages improves the clarity of this chapter. Naturally, the two-stage formulation and solution method can be extended to more stages, if needed.

4.2 Problem statement

In this thesis, the multistage DNP problem aims to identify optimal investment decisions considering conventional (transformers and lines) and non-conventional (contracted flexibility) expansion measures over several planning periods, here illustrated and exemplified with two periods.

That is, investments in network expansion are allocated over time so as to achieve the minimum cost of accommodating the expected load growth in each stage of the multistage planning problem. The resulting multistage expansion plan must take into account all operational and investment constraints. Operational constraints are those technical limits that ensure the safe operation of the DN while respecting the design limits of the primary equipment of a power system. Investment constraints are those that limit investment in parallel lines or transformers at a given network location, and the fact that investment in conventional expansion assets such as transformers and lines must also be paid for in the second planning stage. Planning over two periods was chosen because it allows better observation of the effects of possible network investment deferrals and the role that flexibility can play in this. Furthermore, the two-stage planning approach allows the model to evolve naturally to account for uncertainty in DNP through multi-scenario analysis. A general problem formulation for multistage DNP using conventional and non-conventional expansion technologies and solutions is presented in Section 4.3.

4.3 Problem formulation

The objective function (OF) minimises the sum of discounted annuities of the investment and operational cost of both planning periods. The annuity represents an annual payment comprised of annual operational cost as well as an annual share of initial investment cost discounted and spread over the lifetime of a grid asset. Annuity calculations, as in equations (4.2-4.12) are used to make investments with different lifetime comparable and account for the value of those beyond the planning horizon.

The binary decision variables contained in equations (4.8 - 4.12), represent investment decisions for transformers ($b_{br_{ij,tra}}$) and lines ($b_{br_{ij,li}}$) as well as contracting of flexibility ($b_{i,fl}$). The problem at hand is subject to multiple constraints, which are described in Section 4.3.1.

4.3.1 Mathematical problem formulation

In the following, the OF of the problem formulated above is described mathematically.

$$\begin{aligned} \min \quad & \sum_{i=1}^{n_{p1}} \frac{1}{(1+r)^i}(A(G_{p1}) + A(F_{p1})) \\ & + \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}(A(G_{p1}) + A(G_{p2}) + A(F_{p2})) \end{aligned} \tag{4.1}$$

where

$$A(G) = A^{inv}(G) + A^{op}(G) \tag{4.2}$$

$$A(F) = A^{op}(F) \tag{4.3}$$

$$A^{inv} = C^{inv}\,\alpha_{n,r} \tag{4.4}$$

$$A^{op} = C^{op}_{li,tot} + C^{op}_{tra,tot} + C^{op}_{fl,tot} \tag{4.5}$$

$$\alpha_{n,r} = \frac{1}{1 - \frac{1}{(1+r)^n}} \tag{4.6}$$

$$C^{inv} = C^{inv}_{li,tot} + C^{inv}_{tra,tot} \tag{4.7}$$

$$C^{op}_{li,tot} = \sum_{br_{ij} \in \Omega_pl} \sum_{li \in \Omega_{li}} b_{br_{ij,li}} \, C^{op}_{li} \, l_{br_{ij}} \tag{4.8}$$

$$C^{op}_{tra,tot} = \sum_{br_{ij} \in \Omega_{ds}} \sum_{tra \in \Omega_{tra}} b_{br_{ij,tra}} \, C^{op}_{tra} \tag{4.9}$$

$$C^{op}_{fl,tot} = \sum_{i \in \Omega_{dr}} \sum_{fl \in \Omega_{fl}} b_{i,fl} \, C^{op}_{fl} \tag{4.10}$$

$$C^{inv}_{li,tot} = \sum_{br_{ij} \in \Omega_{pl}} \sum_{li \in \Omega_{li}} b_{br_{ij,li}} \, C^{inv}_{li} \, l_{br_{ij}} \tag{4.11}$$

$$C^{inv}_{tra,tot} = \sum_{br_{ij} \in \Omega_{ds}} \sum_{tra \in \Omega_{tra}} b_{br_{ij,tra}} \, C^{inv}_{tra} \tag{4.12}$$

Investment and operational constraints

The OF is subject to the following investment and operational constraints.

$$h_1(G_{p1}, F_{p1}) \geq 0 \tag{4.13}$$

$$h_2(G_{p1}, G_{p2}, F_{p2}) \geq 0 \tag{4.14}$$

Where h_1 and h_2, shown in equations (4.13) and (4.14), are generic functions representing all investment and operational constraints in period 1 and period 2, respectively. These constraints are described in the following.

Within a single planning period, an upper boundary for investments in conventional expansion is limiting the number of parallel lines per power line branch as well as the number of parallel transformers per distribution substation branch.

Between the individual planning periods, constraints ensure that investments in conventional expansions made in the first period (i.e G_{p1}) are also accounted for, together with the additional investments in the second period (i.e G_{p1} and G_{p2}). This is due to the fact that grid assets, such as lines and transformers, once installed are usually not removed until the end of their useful life. On the contrary, flexibility can be contracted in shorter intervals, depending on the short-term planning of the distribution system operator. Therefore, annuities of flexibility (i.e. F_{p1}, F_{p2}) are only accounted for in the planning period that the flexibility is also contracted.

As the DNP problem considers the peak-load in the network as the relevant time slice for planning (Teichgraeber et al., 2022; Mateo, Gomez San Roman, et al., 2011), constraints describing operational limits of network assets have to be hold at these peak times. That means all common power flow equations must be solved and the following operational constraints be hold. The bounding constraint describing the permissible voltage at any node, equation (4.15), and the inequality constraint describing the maximum current on any branch, equation (4.16), are formulated.

$$V_i^{min} \geq V_i \geq V_i^{max} \quad \forall i \in \Omega_b \tag{4.15}$$

$$I_{br_{ij}} \leq I_{br_{ij}}^{max} \quad \forall ij \in \Omega_{br} \tag{4.16}$$

Additionally, full network connectivity (i.e. no unsupplied loads or network assets exist) is ensured at all times by a network connectivity constraint. This means that all nodes and consequently all loads are connected and none remains isolated. The network radiality constraint ensures that the network remains radial after new transformers and lines are added. Complying with all network operational constraints is ensured by power flow and graph analysis. As only feasible solutions are considered, the value of lost load is not part of the OF, shown in equation (4.1).

4.4 Solution method: Pseudo-dynamic planning

The methodology applied to solve the two-stage DNP problem described in Section 4.3, is specified in the following. At the core of the multistage DNP model lays a single-stage DNP model based on the TS metaheuristic, which is described in Section 3.4.

The solution method for the two-stage DNP problem is the pseudo-dynamic planning approach called forward fill-in, mentioned in Section 2. Within this methodology, the TS-based single-stage DNP model, described in Section 3.4, is applied for each planning period until the end of the planning horizon. Firstly, as shown in Figure 4.1, the initial network at the beginning of period 1 is populated with new loads, according to the load growth in stage 1. This is followed by a run of the single-stage DNP model (i.e. Step 1), determining the optimal set of conventional (transformers and lines, i.e. G_{p1}) and non-conventional (flexibility contract contracting, i.e. F_{p1}) expansion measures that satisfy the load growth of period 1. The resulting network is then used as input for the second planning period, while the flexibility contracts activated in stage 1 are deactivated and the network is populated with additional loads according to the network load at the end of period 2. As before, the single-stage DNP model is then applied (i.e. step 2), yielding the set of conventional (i.e. G_{p2}) and non-conventional (i.e. F_{p2}) network expansions. In the case of more stages, this procedure would be repeated until the year of the planning horizon is reached.

The forward fill-in approach was also chosen because it is easier to extend the solution method for multistage DNP problems to multistage DNP under uncertainty. By employing the forward fill-in approach, the decision making can naturally adapt to the evolving uncertainties along the planning stages towards the planning horizon. Using a backward approach, as discussed in Section 2.1, the investment decisions at each stage would be preconditioned by the initial decisions made for the planning horizon, where uncertainty is greatest.

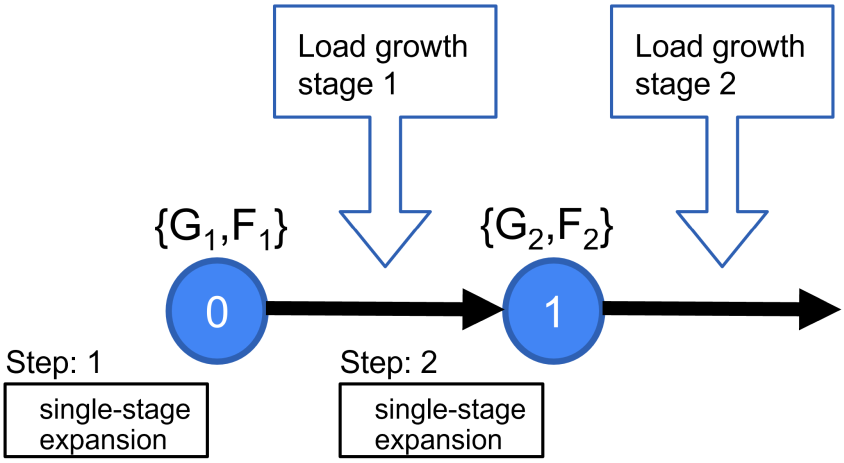


Figure 4.1: Pseudo-dynamic multistage planning: forward fill-in

4.5 Case study

In this section, the assumptions and their modelling for the case study are described, combining the modelling of the initial network, the modelling of a load growth scenario as well as the modelling of conventional and non-conventional network expansion.

4.5.1 General modelling assumptions

The network operational constraints are implemented as follows. The voltage limit is set to +/- 10 % of the nominal voltage. The current capacity limit is set to 100 % of each asset's nameplate capacity.

The discounting rate used in the economic evaluation of the investment decisions is based on the Weighted Average Cost of Capital (WACC) and is set to 6 %. Based on Spanish regulation (Comisión Nacional de los Mercados y la Competencia, 2019) the regulatory expected lifetime of transformers and power lines is set to 40 years. The investment and maintenance cost for conventional network expansion is based on State Gazette no. 297 (Ministerio de Industria, Energía y Turismo, 2015).

Contracted flexibility is formulated as an estimated annual capacity price, that indirectly entails the cost of energy used during the activation of the contracted flexibility. Flexibility contracting costs are set to 10 €/kW per year. This value has been selected from a range given in (UKPN, 2021; SP Energy Networks, 2022).

4.5.2 Initial network

The initial network used as input to this model is created applying the Greenfield RNM (Mateo, Gomez San Roman, et al., 2011; Mateo, Prettico, et al., 2018). The Greenfield RNM is able to create large-scale realistic network models based on high-level demographic data, electricity consumption data and geographic data from OpenStreetMap.

The network model shown in Figure 4.2 is an MV/LV-feeder located in the North-East corner of a realistic network model of Albacete, Spain. The feeder contains 5 MV/LV distribution substations with respective LV feeders. The two voltage levels are rated at 20 kV (MV) with 5 buses and 1.196 km of power lines as well as 0.4 kV (LV) with 91 buses and power lines of 2.718 km in length. The total nameplate capacity of the 5 transformers in the 5 DS is 2.540 MVA. The 86 loads in the initial network create a peak demand of 1.565 MW and 0.467 Mvar. The time slice relevant for peak-load expansion planning is estimated using simultaneity factors applied to individual consumer peaks, as described in (Mateo, Gomez San Roman, et al., 2011).

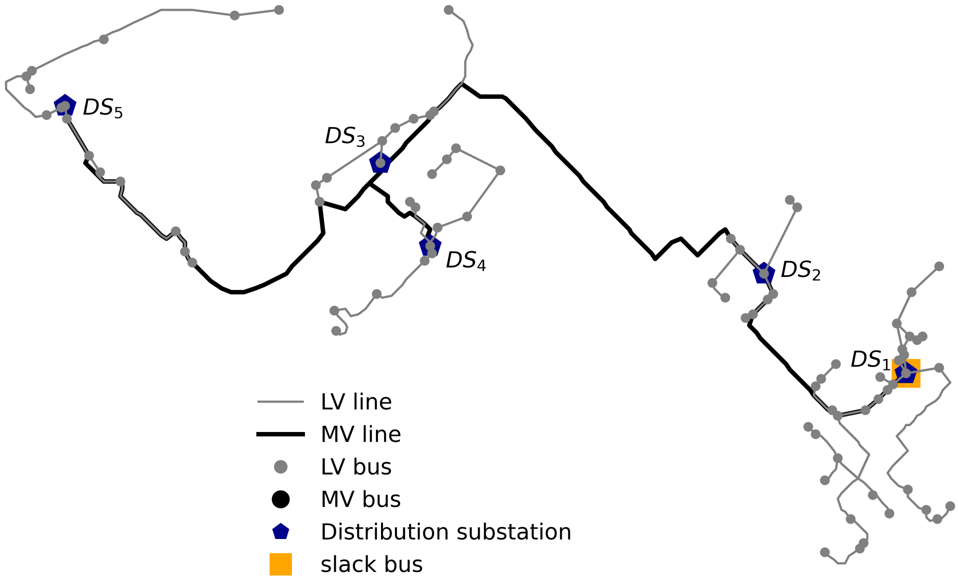


Figure 4.2: Plot of MV/LV feeder before expansion

4.5.3 Load growth scenario modelling

The modelled load growth represents a scenario with high electrification of the transport sector. Three types of EVC are randomly added to the LV network. In the first period, 105 EVC with a rating of 3.7 kW and 8 rated at 11 kW are added, resulting in a peak-load growth of 0.477 MW. In the second period, another 105 EVCs with a rating of 3.7 kW, 26 EVCs rated at 11 kW as well as 5 rated at 22 kW are added, resulting in an additional peak-load growth of 0.785 MW. This results in an overall load growth of 30.65 % in the first period. The overall load growth in the second period is 38.61 %. Both periods constitute 13 years each.

4.5.4 Network expansion modelling, conventional measures

The network expansion options are classified as conventional (transformer and power line expansion) and non-conventional (flexibility contracting) options. Transformer expansion options comprise the installation of parallel transformers as well as the exchange (upgrade) of transformers with a bigger capacity, or a combination of parallel addition and exchange. In conformity with the

State Gazette no. 297 of 12 December 2015 (Ministerio de Industria, Energía y Turismo, 2015), four standard capacities of three-phase transformers are available for expansion, namely 250 kVA, 400 kVA, 630 kVA and 1000 kVA. The upper boundary describing the maximum parallel transformers per distribution substation branch is set to 3 in this case study. Power line expansion options are modelled by parallel additions of power lines, of equal capacity as the existing line, on the respective power line branches. The constraint describing the maximum parallel additions of lines per power line branch is set to 3 in this case study.

4.5.5 Network expansion modelling, non-conventional measures

In this case study, flexibility contracting as a non-conventional expansion option is modelled as follows. Loads with contracted flexibility reduce their peak-load contributing capacity by 50 %. Half of the loads of the initial network, randomly selected, as well as all additional EVC loads, are assumed to be contractable. This results in a potential total peak-load reduction of 0.619 MW in the first period as well as 1.011 MW in the second period. Flexibility is activated per bus, i.e. when flexibility is activated on a specific bus of the network, all available flexibility contracts connected to that bus are activated.

4.6 Results and discussion

Firstly, the results of the two-stage planning approach applying only conventional expansion measures are presented. Secondly, the results using conventional as well as non-conventional expansion utilising flexibility contracting are shown. An overview of the results obtained with the forward fill-in approach is given in Table 4.3, showing the network evolution in the two cases. In addition, Table 4.4 shows the respective evolution of the net present value (NPV) of the total costs.

4.6.1 Two-stage planning without flexibility contracting

Applying the two-stage planning methodology for the case only with conventional expansion measures, as described in Section 4.5.4, results in the network expansion shown in Table 4.3 which are described in the following.

In period 1, the total LV power line length is expanded by 0.100 km and the transformer capacity is expanded by 550 kVA, by exchanging one transformer (i.e. from 250 kVA to 400 kVA) and adding one 400 kVA transformer in parallel to an existing 1000 kVA transformer, as shown in Table 4.1. The resulting network, with the expansions of the first period highlighted in red, is shown in Figure 4.3.

In period 2, the LV circuitry is expanded five-fold with an additional 0.500 km and 3 transformers are upgraded (exchanged) adding a total capacity of 690 kVA, as shown in Table 4.1. The resulting network, with the expansions of the second period highlighted in red, is shown in Figure 4.4.

For each period, the NPV of the total cost as well as the cost by expansion type is shown in Table 4.4. These costs for the individual periods result in the NPV of a total cost of 133,460 € for all planning periods.

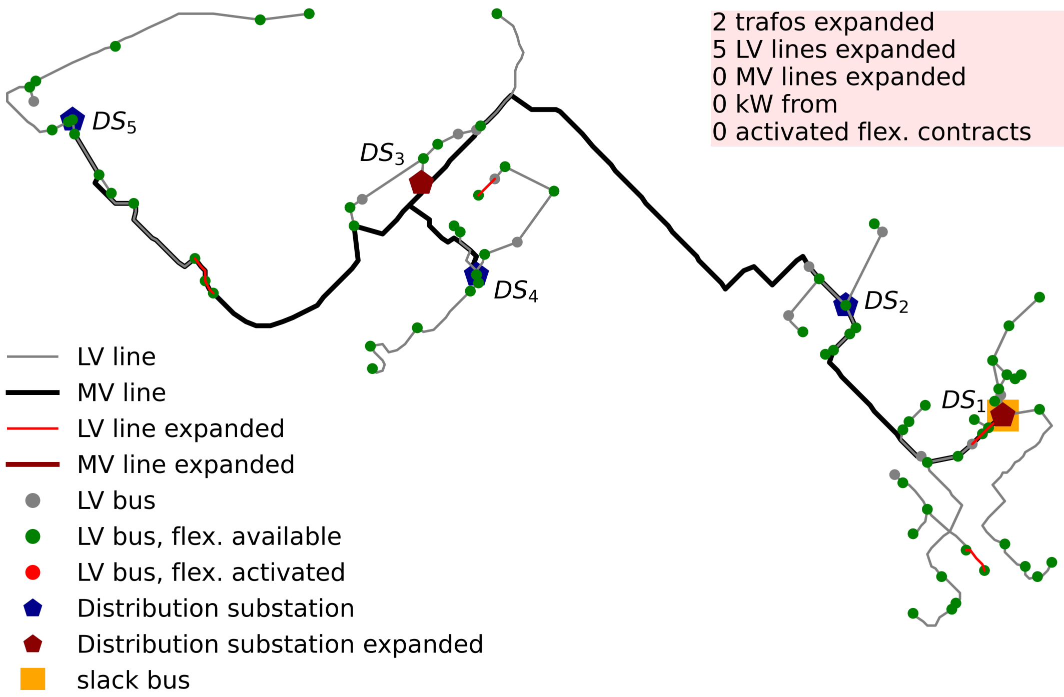


Figure 4.3: Network expansion plot without flexibility activation, period 1

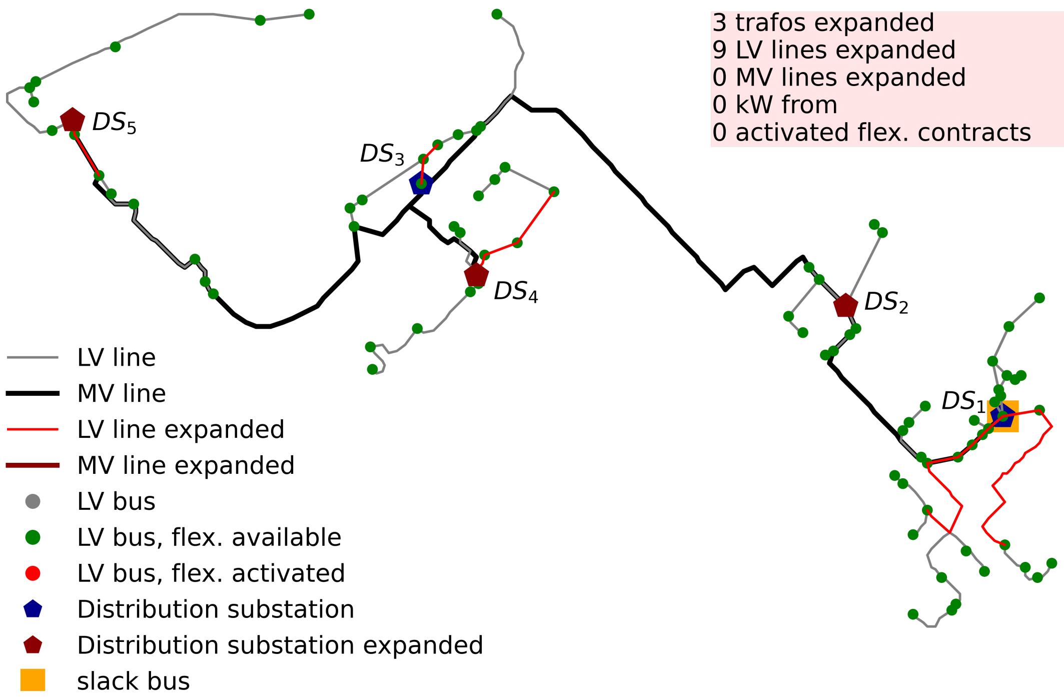


Figure 4.4: Network expansion plot without flexibility activation, period 2

transformers [kVA] at distribution substation	DS_1	DS_2	DS_3	DS_4	DS_5
initial year	1000	400	250	400	400
period 1	1000 400	400	400	400	400
period 2	1000 400	630	400	630	630

Table 4.1: Evolution of installed transformers [kVA] at distribution substations, case without flexibility contracting

4.6.2 Two-stage planning with flexibility contracting

Applying the two-stage planning methodology as in the previous case but adding flexibility contracting as a non-conventional expansion measure, as described in Section 4.5.5, results in the network expansion shown in Table 4.3 which are described in the following.

In period 1, the LV line circuitry is expanded by 0.100 km, as in the previous case, though the transformer capacity is only expanded by 400 kVA, by adding one transformer in parallel to an existing one, as shown in Table 4.2. Additionally, 67.53 kW of flexibility is contracted as a non-conventional expansion measure. The resulting network, with the expansions of the first period highlighted in red, is shown in Figure 4.5.

In period 2, the LV circuitry is expanded by 0.330 km and 4 transformers are upgraded (exchanged) adding a capacity of 840 kVA, as shown in Table 4.2. Also, 56.21 kW of flexibility is contracted in this period. The resulting network, with the expansions of the second period highlighted in red, is shown in Figure 4.6.

For each period, the NPV of the total cost, as well as the cost by expansion type, are shown in Table 4.4. These cost for the individual periods results in the NPV of the total cost of 112,539 € for all planning periods. Therefore, in this case study the usage of flexibility contracting at a cost of 10 €/kW per year results in total cost savings of 15.68 %.

As shown in Tables 4.1 and 4.2, the application of flexibility contracting reduces the needed transformer expansion in the first period by 1 transformer upgrade of 150 kVA. This results in transformer expansion cost savings of 26,451 € while adding 5,978 € in cost for flexibility contracting, as shown in Table 4.4. The NPV of total cost savings in the first planning period, due to flexibility contracting is therefore 20,473 €.

In the second period, the additional load growth makes all transformer upgrades necessary, that were also done in the case without flexibility contracting. This happens, even while a comparable amount of flexibility is contracted also in this period. Notably, the line expansion is lower in this stage and therefore in the overall expansion, as can be observed especially in the lower right corner of Figure 4.6. This results in total expansion costs for the second period that are overall 0.16 % lower than in the case without flexibility contracting. Due to the time value of money, postponing

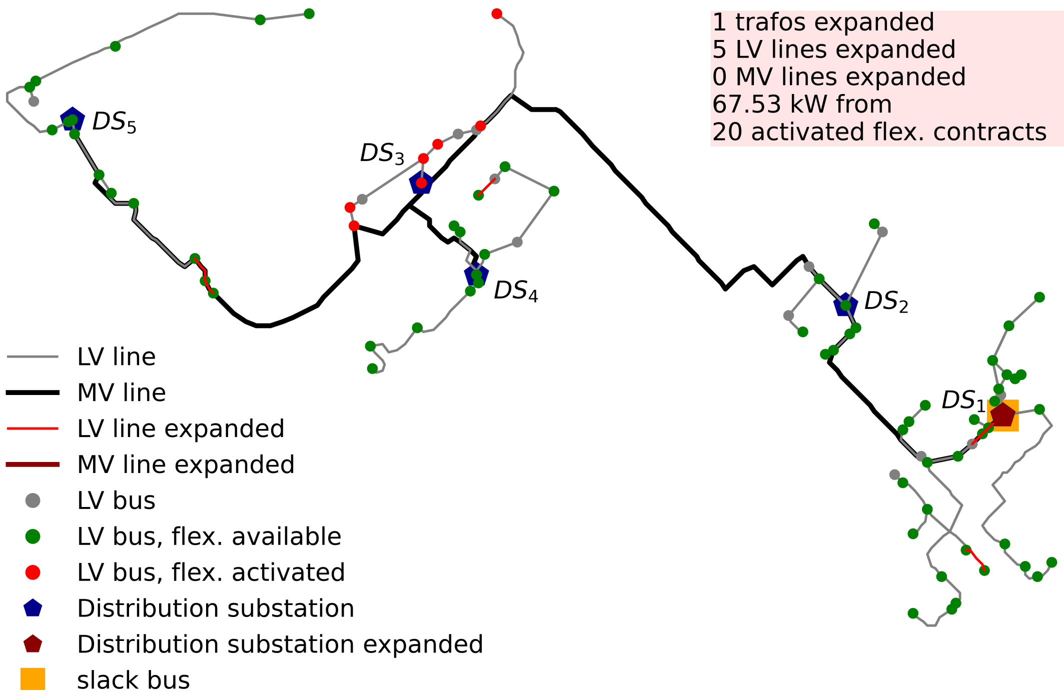


Figure 4.5: Network expansion plot with flexibility activation, period 1

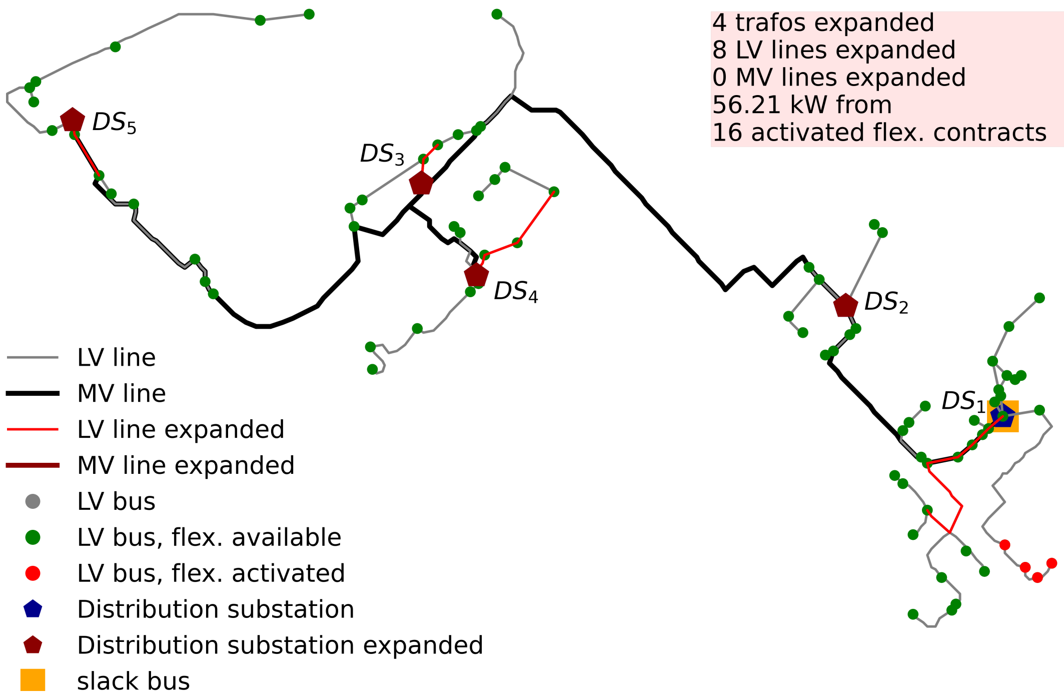


Figure 4.6: Network expansion plot with flexibility activation, period 2

transformers [kVA] at distribution substation	DS_1	DS_2	DS_3	DS_4	DS_5
initial year	1000	400	250	400	400
period 1	1000 400	400	250	400	400
period 2	1000 400	630	400	630	630

Table 4.2: Evolution of installed transformers [kVA] at distribution substations, case with flexibility contracting

transformer expansions from the first to the second period saves costs in transformer expansion of 26,452 € or 22.02 %. Also, overall line expansion costs are reduced by 2,779 € or 20.89 %, while additional costs of 8,311 € occur for flexibility contracting. This results in overall cost savings of 20,921 € or 15.68 % that are enabled by flexibility contracting.

		no flexibility		with flexibility	
	initial year	period 1	period 2	period 1	period 2
$P_{load,tot}[MW]$	1.555	2.031	2.816	1.964	2.760
Transformers					
count	5	6	6	6	6
capacity $[MVA]$	2.45	3	3.69	2.85	3.69
Power lines					
MV circuitry $[km]$	1.196	1.196	1.196	1.196	1.196
LV circuitry $[km]$	2.718	2.821	3.223	2.821	3.05

Table 4.3: Results of two-stage planning with forward fill-in method with and without flexibility contracting.

4.6.3 General findings

The multistage model applied for a two-stage DNP has shown several interesting effects that are valuable to support investment decision-making. Firstly, the two-stage planning approach enables one to observe the time value of money, as some investments can be postponed to a later point in time when the load growth makes it necessary. In single-stage models, the investment time is

	no flexibility			with flexibility		
	period 1	period 2	total	period 1	period 2	total
NPV:	58,402	75,058	133,460	37,929	74,610	112,539
of which:						
Transformers	54,870	65,284	120,155	28,419	65,284	93,703
Power lines	3,532	9,774	13,305	3,532	6,993	10,525
Flexibility	0	0	0	5,978	2,333	8,311

Table 4.4: NPV of total cost [€] with forward fill-in method with and without flexibility contracting.

assumed to be at the beginning of the planning period; therefore, the scope of possible savings due to network investment deferrals is not expressed.

Secondly, the two-stage DNP approach shows the utility of multistage planning models to uncover the value of load flexibility in DNP. On the one hand, flexibility contracting can help to defer network investments. On the other hand, the use of flexibility contracting can avoid investing in the same network segment too often. That is, the load growth in consecutive stages can lead to non-optimal expansion decisions in a given segment of the network, making consecutive network expansions for example in the same distribution substation necessary. Flexibility contracting can help to avoid such premature conventional expansion decisions, covering some of the load growth in the first stage, while a conventional expansion decision can still be taken in the second stage. This is demonstrated by applying the multistage model to investment cases without flexibility contracting, as in Section 4.6.1, and with flexibility contracting, as in Section 4.6.2. Comparing the transformers in distribution substation DS_3, shown in the feeder in Figure 4.3 and Figure 4.5 as well as in Tables 4.1 and 4.2, it can be seen that flexibility in the LV feeder below the transformer can avoid the need for an expansion in the first stage.

4.7 Conclusion

In this chapter, pseudo-dynamic multistage DNP using flexibility contracting as an alternative to conventional network reinforcement has been implemented. The multistage DNP problem can be seen as an extension of the single-stage DNP problem and the solution method introduced builds on the solution method presented in the previous chapter. Using the forward fill-in approach as a pseudo-dynamic algorithm together with TS as a metaheuristic single-stage planning algorithm does not guarantee optimality, but it shows to work well and provides interesting results. Also, it is easily scalable to solve DNP problems with realistic large-scale distribution systems. The multistage approach clearly demonstrates the value of flexibility in long-term DNP. Flexibility contracting helps to defer costly network investments with long asset lifetimes to the future, where the time value of money is lower and the required investment is more justified with respect to expected load growth. In the case study, flexibility contracting at a cost of 10 €/kW per year results in total cost savings of 15.68 %. As the forward fill-in method, described in Section 4.4, is a pseudo-dynamic planning method, some time-dynamic effects might not be captured. Therefore, it is recommended to investigate alternative multistage pseudo-dynamic or ideally dynamic algorithms in future research, for the problem at hand.

5 Distribution network planning under uncertainty

This chapter discusses how the previously developed models can be extended for distribution network planning under uncertainty. First, an overview of uncertainty and risk relevant to distribution network planning and related solution methods is given. Then, the problem formulation and a solution method for single-stage multi-scenario distribution network planning are presented. Thereafter, the problem is extended to multistage multi-scenario distribution network planning and a corresponding problem formulation and solution method is presented. The solution method for multistage multi-scenario planning is then applied in a case study with two stages and two scenarios. Finally, the obtained results are discussed and conclusions are drawn.

5.1 Multistage distribution network planning with and without flexibility

The previous chapters dealt with optimal investment decisions in conventional and non-conventional network expansion measures for the network to meet expected load growth, mainly due to electrification of transport (i.e. EVCs) and heating (i.e. HPs). So far, the previous chapters have dealt with decisions on the location and size of new network assets or non-conventional expansion solutions (i.e. flexibility contracting) and their timing in a multistage DNP. Section 1.1 discusses the uncertainties associated with the transformation of the energy system and Section 1.1.1 discusses those particularly relevant to the electric distribution system. Inevitably, the logical next step is to extend the multistage DNP problem to cover uncertainty in long-term planning. Over the next few decades, it is generally expected that a large number of new DER will be connected to the DN. However, many uncertainties remain, mainly due to non-linear technological developments, an unpredictable macro-economic environment as well as speculative socio-economic trends that need to be considered in DNP. Therefore, this chapter extends the long-term, multistage DNP problem, considering flexibility as non-conventional network expansion measures, by the dimension of uncertainty. After a discussion of uncertainty and risk and a general review of solution methods for planning under uncertainty, the problem of DNP under uncertainty is specified. Finally, in order to deal with uncertainty in long-term DNP planning and to investigate the value of flexibility contracting in such planning, the multistage DNP model introduced earlier is combined with multi-scenario analysis.

5.2 Risk and uncertainty

The future is fundamentally uncertain, so planning exercises need to deal with the relevant uncertainties contained within the planning horizon or, more generally, the future. Due to multiple factors, the further one looks into the future, the greater the uncertainty. Some of these factors are complexity (Strand, 1999; Holland, 2006; Schoemaker, 2004), inter-dependency (Arthur, 1989; Hämäläinen et al., 2016), feedback-loops and delays (Lane et al., 1997), incomplete information (Montero et al., 2010; Ferson et al., 1996), unforeseeable events (i.e. black swans (Taleb, 2007)). Naturally, in complex systems, these factors are strongly interrelated, as complexity can be defined by a large number of variables and their interrelation (Schoemaker, 2004). For example, inter-dependency and feedback-loops (including non-linearity) are part of what makes a system complex, supporting the first mentioned factor. Incomplete information and unforeseeable events refer to the information that is available about a system and its past states (i.e. incomplete information), or even accessible at all (i.e. unforeseeable events).

Although the terms risk and uncertainty are sometimes used interchangeably, the distinction is important. In general, uncertainty represents a lack of certainty about something. Uncertainty ranges from a slight lack of certainty to a complete lack of conviction or knowledge, especially about outcomes or results. Risk can be described as an uncertainty that inherently carries a certain probability, so a risk can be described in terms of the likelihood of an uncertain event occurring (Morgan et al., 1990). Practically, risk implies future uncertainty about a deviation from expected earnings or expected outcomes in general. Uncertainty, where probability estimates are not calculable and little more is known about possible outcomes are called deep uncertainty (Lempert, 2002; Walker et al., 2013) or severe uncertainty (Ben-Haim, 2006). The availability of sufficient information about a system variables, which may allow to derive stochastic models about the system, is one key criteria to decide on the decision making technique. Additionally, in real-world decision making, decisions are often sequential, such as multistage DNP. That is, they are rarely completely unrelated. Therefore today's choices affect the set of available decisions in the future, in other words, the decisions today open and close future options as well as affect the information available in the future (Keeney, 1982).

5.3 Overview of problem formulation and solution methods for planning under uncertainty

To handle uncertainty (and risk), the discipline of operations research is making use of various methodologies. Methods to handle uncertainty and risk can be categorised as quantitative and semi-quantitative methods (Ioannou et al., 2017). While quantitative methods are applied for cases where statistical information is available and all probability distributions or variances are assumed to be known, semi-quantitative methods can include uncertainty for which statistical information is not provided (i.e. expert opinions on macro-economic or technological developments). Quantitative methods include Monte Carlo simulations (MCS), real option analysis (ROA) and mean-variance portfolio, stochastic optimisation and other stochastic modelling techniques (Ioannou et al., 2017). Semi-quantitative methods are multi-criteria decision analysis (MCDA), scenario analysis, sensitivity analysis and robust optimisation or robust decision making in general (Ioannou et al., 2017). In addition to scenario analysis, scenario planning is a related but distinct method. Scenario analysis is based on pre-defined scenarios that represent the uncertainty within the planning horizon. These scenarios, considered as sub-problems, are then studied with the aim of coming up with a well-hedged solution to the overall problem (Rockafellar et al., 1991). Though, some argue that scenario analysis often does not systematically use quantitative information to correct for fallacies in reasoning caused by humans (Lempert, 2002). In contrast to scenario analysis, scenario planning inherently involves the exercise of scenario generation (Schoemaker, 2004). A classic paper on power system planning under uncertainty considers scenario planning as one of three general solution methods (Gorenstin et al., 1993). The other two are considered to be stochastic optimisation and DE, which are closely related as described in Section 5.3.1.

5.3.1 Stochastic optimisation

Stochastic programming is a mathematical programming approach under uncertainty, where the uncertainty can be formulated probabilistically. Stochastic programming is concerned with minimising or maximising the objective function of a problem where some parameters of the objective function are uncertain and this uncertainty is expressed probabilistically. This means that stochastic programming is concerned with finding solutions (or policies) that are feasible for (almost) all possible realisations of the uncertain parameters. In such stochastic programs, where some uncertain parameters are modelled probabilistically in the constraints, one speaks of chance-constrained programming (Li et al., 2021). The uncertainty in the problem must be expressed in terms of a known or estimable probability distribution. In stochastic programming, the OF contains some formulation of expected value that represents the uncertainty of the problem. Therefore, stochastic programming is sometimes referred to as a risk neutral approach (Li et al., 2021). The uncertainties of the problem, expressed in terms of probabilities, are usually transformed into an equivalent set of scenarios, using approximation techniques. This critical process is called scenario construction or scenario generation.

Multistage stochastic programming is concerned with stochastic programming for multistage problems, with its best-known case being the two-stage program. In such problems, a first-stage decision is to be made before some uncertainty materialises, followed by a second-stage (or usually later) recourse decision with the aim of potentially improving the outcome of the earlier decisions. The result of two-stage and multistage stochastic programs is a policy tree consisting of first-stage decisions (*here-and-now*) followed by some recourse decisions (*wait-and-see*).

One way to solve stochastic optimisation problems is to create a DE formulation of either the OF, the constraints, or both (Birge et al., 2011; Li et al., 2021). This effectively removes the probabilistic nature of the problem by replacing the uncertain parameters with their expected or other representative values. The resulting problem can then be solved using a conventional deterministic optimisation method (Muñoz-Delgado et al., 2016; Asensio, Meneses de Quevedo, et al., 2018). However, for problems with higher dimensionality, and especially for cases where continuous random variables are discretised, other solution methods become more promising. In the DE solution method, the uncertainty over the stages of a multistage problem is modelled in scenario trees, while other solution methods rely on a scenario lattice in which the event space is discretised (Gorski, n.d.; Popović et al., 2010). As the DE solution method does not scale well with the number of stages and scenarios involved in scenario-based multistage stochastic programming, decomposition techniques are regularly applied (Aldasoro et al., 2017). A common decomposition approach applied in such complex problems is that of decomposing the multistage problem by stages. A popular approach of this kind is a variation of Benders decomposition called the L-shape approach (Hemmi et al., 2018; Aldasoro et al., 2017). Opposed to this approach, a scenario decomposition technique aims at decomposing the problem by scenarios, therefore creating smaller, solvable DE sub-problems (Hemmi et al., 2018). These sub-problems can then be solved relatively fast within a recursive algorithm named *Evaluate* & *Cut*, leading to promising results with respect to computation time and scalability.

5.3.2 Scenarios and their generation

A scenario is a dynamic set of events that can be described in a scenario tree. A broader definition of a scenario is a description of possible future states or a description of developments into the future. Among the various scenario typologies that have been described, the one presented by (Börjeson et al., 2006) seems particularly applicable in ESP and DNP. Within this scenario typology, three main categories of scenario studies are described; predictive scenarios, which try to describe likely future situations; explorative scenarios, which focus on the proposition of more alternative developments; normative scenarios, which propose different states or pathways to fulfil specific targets. The later, normative scenarios are particularly relevant in this work, as energy system scenarios are often based on achieving political and/or environmental targets, such as economic growth and efficiency as well as carbon emission reduction. It is important to distinguish between the broader field of scenario development or scenario planning in future studies, a good overview is given in (Bishop et al., 2007), and the specific case of scenario or scenario tree generation in stochastic programming. In the latter case, uncertainty is modelled probabilistically and the generation methods are much more mathematical or numerical in nature, that is statistical information and the knowledge about physics of a system and their respective processing is of more relevance than the influence of experts' opinions in the modelling of uncertainty. To model uncertainty, stochastic programming relies on known or estimated probability distributions. Depending on the problem, constructing scenarios from the possible realisations of the uncertain parameters can lead to a tractable problem (i.e. a random vector with known probabilities) or rather make the problem numerically intractable (i.e. a large or infinite number of scenarios). Reducing the number of scenarios can make the problem tractable, though the solution looses in accuracy compared to the real problem. Therefore, a trade-off exists between the scenarios representativeness of the real problem and the computational tractability of the problem. One attempt to reconcile this trade-off is to randomise the uncertain variables, constructing a reduced but representative set of scenarios using Monte-Carlo sampling techniques (Shapiro et al., 2007). Other techniques are more concerned with the manipulation of the scenario tree by aggregating nodes and stages, trimming and refining of trees and other reduction techniques (Dupačová et al., 2000). Several general methodologies for scenario tree generation for multistage stochastic optimisation is introduced by (Dupačová et al., 2000), where inter-dependencies between stages is allowed, which is very relevant in multistage DNP under uncertainty.

In addition to stochastic methods, a common approach to support decision problems under deep (or high) uncertainty and high complexity (Schoemaker, 2004), is the use of scenario planning. The author also argues that the focus of planning under uncertainty should often be more on the uncertainties and complexities inherent in a forecast (i.e. a single scenario assuming perfect foresight) than on the respective point estimates of uncertain parameters. That is, not to focus on the attempt to identify the single value in the parameter space that supposedly *best* represents the uncertainty of the respective parameter. Scenario planning aims to provide a limited set of internally consistent scenarios by attempting to control for interdependencies between relevant factors and analyst biases, combining the known with the unknown (Schoemaker, 2004). It is important to note that, unlike stochastic methods, the scenarios used in scenario planning may or may not contain elements of probability. That is, scenarios or scenario trees are modelled in a possibilistic way, but may contain probabilistic elements.

5.3.3 Robust optimisation

Robust optimisation is a mathematical optimisation approach that aims to find the best solution for the worst case of the modelled uncertainty. In robust optimisation, the modelled uncertainty is possibilistic, i.e. no probability distributions need to be known. The origin of robust optimisation is around Wald's maximin regret paradigm, where the maximum result of the worst case (minimum) is sought (Wald, 1950; Sniedovich, 2016). In the case of a minimisation problem, as all DNP problems in this thesis are, the paradigm changes to minimax regret, where the best solution (minimum) of the worst case (maximum) is sought. The optimal, robust solution to the DNP problem found by the minimax decision criterion is therefore the solution that provides the least cost expansion plan under the worst case scenario. It is particularly suited to problems where solutions have a high cost of failure, but is sometimes criticised for producing overly conservative solutions.

5.3.4 Other methods for decision-making in planning under uncertainty

Risk aversion of the planner can have a major influence on what method is chosen for planning under uncertainty. Among the solution methods, risk aversion increases from Stochastic programming (i.e. risk neutral), through chance-constraint programming (ie. risk averse), to robust optimisation (i.e. worst case scenario) (Li et al., 2021). In addition to those methods, a number of other methods are available for decision support under uncertainty. Such methods can be particularly useful when combined with scenario planning or scenario generation that is appropriate to the underlying problem and the risk aversion of the planner.

Other authors propose a risk analysis approach to distribution planning to be used instead of stochastic optimisation, representing the authors risk-averse perspective on the planning problem (Miranda and Proenca, 1998). It is argued that an approach of risk analysis produces a lower likelihood of risky decisions, as the decision making is more concerned with preparing for the impact of multiple scenarios rather than optimising for the average of the scenarios. That is, expected risk due to possible changes in the underlying assumptions is minimised by designing efficient strategies for adaption, such as minimising regret or hedging strategies against multiple possible futures. An interesting approach combines risk analysis with MCDA to incorporate deep uncertainties affecting economic and environmental objectives and the associated risk aversion of stakeholders (Linares, 2002). This model addresses risk at two levels. At the first level, MCDA and multi-objective optimisation are used to arrive at efficient solutions that take into account environmental and economic objectives. At the second level, the preferred solution is selected through risk analysis using a decision criterion such as Wald's minimax or Savage's minimum regret.

As scenario analysis captures only uncertainty in the generated sets of scenarios, once problems are very complex, uncertainty stemming from the models itself should be considered as well. To solve this problem Computer Assisted Reasoning was invented (Bankes et al., 2001). Computer Assisted Reasoning uses an ensemble of input scenarios as well as an ensemble of models to derive a large set of possible outcomes (i.e. experiments) that then can be evaluated by expert decision makers. The model promises interesting insight in complex policy problems under deep uncertainty to identify robust policies, given that a diverse set of models is available as input to the method (Lempert, 2002).

Others apply robust decision making theory to water management under deep uncertainty of climate change impact (Lempert and Groves, 2010), which could be used for DNP problems as well. Specifically, a so-called vulnerability-and-response-option analysis is used, which involves generating a large number of possible strategies for which then vulnerabilities and potential response options are then assessed.

5.3.5 Concluding the review

Due to the dominance of deep uncertainty in long-term DNP, approaches of scenario analysis/planning and related methods are more promising to deliver interesting and actionable results. This is not to say that a probabilistic approach should not be used as well. If sufficient historical data is available, a DNP approach based on scenario analysis could also incorporate short-term uncertainties using known probability distributions. This seems particularly relevant for multi-objective optimisations that consider not only the cost of expansion but also the reliability of solutions.

Based on the methods described above, a generally promising approach can be described in three steps, as shown in Figure 5.1. In the first step, the problem is formulated, including all relevant objectives, model parameters, decision variables, constraints and uncertainties in long-term DNP, including the uncertainty modelled in a scenario tree. In the second step, a set of efficient solutions is computed using an optimisation approach appropriate to the problem at hand. In the third and final step, a selection technique is applied to identify the solution preferred by the planner. Based on appropriate preferences, this selection technique can be based on criteria such as robustness, minimax (Wald) or minimum regret (Savage) or simply the selection of the least-cost candidate obtained in the previous step.

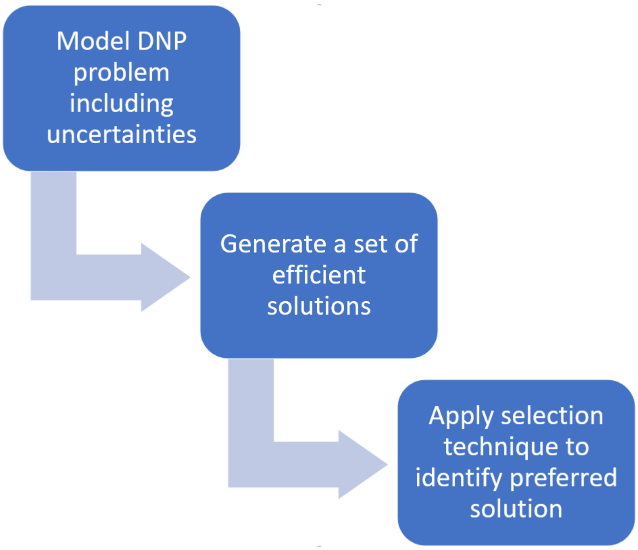


Figure 5.1: General three step solution method for long-term DNP

5.4 General problem formulation for long-term active distribution network planning under uncertainty

In DNP under uncertainty, the representation of the electrical system and the economic decision making might be sufficiently precise to represent a possible future (i.e. a single scenario) well. That is under the assumption of perfect foresight, a DNP model can accurately predict the outcomes of a given set of future events (i.e. a scenario) and therefore assist in decision making. A deterministic DNP model that provides optimal expansion plans assuming perfect foresight within a given scenario, can therefore only be a part of the equation in long-term DNP under uncertainty. The deep uncertainty in long-term DNP is a result of the input parameters (such as technological breakthroughs, resource availability and prices, cost of capital and regulatory stability). Many DNP problems are formulated with multiple objectives. The most common additional objective in multi-objective DNP is reliability. Reliability is not dealt with in this thesis, therefore uncertainties related to reliability (i.e. uncertainties related to faults and asset failure) are not investigated further. An interesting overview of risks in the renewable energy investment sector, that can be seen as a subset of risks in ESP and therefore DNP is given in Table 1 of (Ioannou et al., 2017). Breaking the various high level uncertainties down into what directly affects the process of DNP, the following list of uncertain model input parameters can be drawn:

- nodal demand
  - installation of new loads and their distribution
  - stochastic behaviour of loads
  - load response to external signals (e.g. price elasticity, response to control signals, etc.)
- nodal feed-in

  - installation of new DER and their distribution (e.g. DGs, bi-directional EVCs, storage systems)
  - stochastic behaviour of DER (e.g. PV feed-in)
  - DER feed-in response to internal or external signals (e.g. own-consumption, local energy management incl. storage, etc.)
- flexibility
  - flexibility contracting cost
  - availability of contractable flexibility (flexibility market liquidity and local distribution)
- expansion asset cost (transformers, lines, etc.)
- interest rate (WACC)

Uncertainty of load and DG can be divided in short-term and long-term uncertainty. While long-term uncertainty is much more challenging to describe and model, short-term uncertainty is usually expressed mathematically as stochasticity.

Regarding short-term uncertainty, the peak-load of households without DG was historically highly correlated with the annual energy consumption. This correlation is steadily weakening, due to the increase of new electric appliances as well as PV installations (Vergnes et al., 2019). The stochasticity of PV and wind based DG affects the operation of the power DN in a comparable way as does the stochasticity of loads. That is their stochastic generation, combined with the stochastic demand, creates a stochastic total consumption or injection at the load buses of the network. The stochasticity of electrical loads is a mature topic in power systems, with significant historical data available and an increasing amount of high quality data available due to smart metering. However, due to the upcoming structural changes of the electrical loads present in DNs (i.e. HP, EVC, DR-loads, smart home applications, and unpredictable emerging consumer technologies), load profiles and their stochastic modelling need to be revised (Proedrou, 2021). Some research in this area is concerned with detailed modelling of loads in households (Fischer et al., 2015; Kairisa et al., 2022), others follow an approach to derive load profiles from measured time-series (Spalthoff et al., 2019; Soenen et al., 2023). Generally, load and DG stochasticity is either modelled based on historical or synthetic data that are in turn based on physical models, or probability distributions are used as a base (Hasan et al., 2019). With regard to PV and wind generation stochasticity modelled as independent standard probability distributions, PV feed-in is commonly modelled using the beta distribution, while wind generation is commonly modelled using a Weibull distribution (Hasan et al., 2019). Unlike the stochasticity of demand, the stochasticity of PV and wind is usually quite uniform across a local DN because the weather is locally relatively homogeneous. An example of an exception can be made for PV generation under certain cloud patterns under which PV feed-in also varies temporarily within local proximity in very short times (Hoff et al., 2010). This short term variation is often not captured by stochastic profiles with hourly or 15-minute resolution, though short-term forecasting models are developed (Urquhart et al., 2015). The localised short term variations of PV feed-in can be of concern for DN operation, affecting for example the lifetime of smart grid assets such as OLTCs due to excessive cycling (Liu et al., 2012). Although, due to the implications on the distribution system operation those short term effects are also relevant for smart grid architecture design, beyond architectural questions they are not of great concern for the DNP. From the perspective of distribution system operation, the sum of all generation and load at each node in the network is what impacts the power flows and therefore if the voltages at nodes and currents in branches of the network remain within their limits. In other words, the interaction of the stochastic profiles of different generators and loads is what ultimately creates the stochastic power flows. One approach to handle the correlation between the stochasticity of DG and demand is based on historical data (Muñoz-Delgado et al., 2016; Asensio, Muñoz-Delgado, et al., 2017). Conventionally, the uncertainty between DG and load is often assumed to be uncorrelated, which is changing with increasing penetration of DG and new loads (Atwa et al., 2011; Hasan et al., 2019). With the increasing number of prosumers trying to increase their own consumption, the emergence of local market schemes and time-of-use tariffs, a coupling of the related uncertainties is expected. Therefore, when modelling short-term uncertainty, the respective stochastic correlation might change which must be taken into account (Hasan et al., 2019).

Long-term uncertainties in load and generation are mostly concerned with the long-term evolution of DER and consumer technologies in a respective DN. Possible future mixes of technologies in DN depend on the general long-term uncertainties described in Section 1.1 (e.g. technological breakthroughs and novel technologies, consumer lifestyles, raw material and product prices and general micro and macro-economic developments). The macroeconomic and technological uncertainties converging into future reality defines many aspects of the energy system with all its consequences for the power system and therefore distribution system. Concrete realities for which the DN needs to be prepared for, comprise the number of EVCs, HPs, PV and DG installations in general, as well as their demand patterns and elasticity to external signals such as flexibility prices.

Uncertainty modelling

In this thesis, uncertainty is modelled in a scenario tree with n_s discrete branches, each with its individual weight σ^s, representing the probability of each scenario. This tree contains all possible realisations of the random variables under consideration. An individual scenario describes a unique path from the root to a leaf of the tree. The root of the tree is indicated as stage 0, where the expansion decisions have to be made to cover the still uncertain load growth in the following period. In general, nodes represent decision points (i.e. investment in lines or transformers or contracting of flexibility) and edges (also called branches) represent realisations of uncertain parameters (e.g. load growth, installation of new DER, changing prices of expansion assets, etc.).

For single-stage problems, such a tree containing all n_s individual scenarios in the set Ω_S, is shown in Figure 5.2.

The weights of all these discrete scenarios must add up to 1, such that equation (5.1) holds. Also, if possibilistic multi-scenario planning is considered, all weights must be equal, such that equation (5.2) holds, for $s \in \Omega_S$, where Ω_S is the set of all scenarios and n_s is the number of scenarios in set Ω_S.

$$\sum_{s=1}^{n_s} \sigma_p^s = 1 \quad \forall s \in \Omega_S \tag{5.1}$$

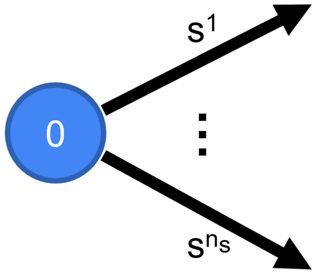


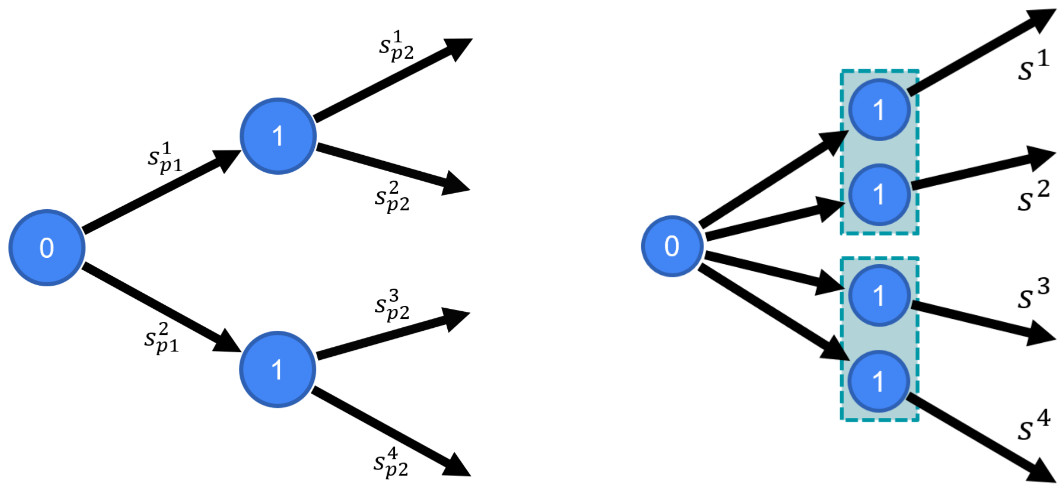
Figure 5.2: Single-stage scenario tree with n_s branches

$$\sigma^s = \frac{1}{n_s} \quad \forall s \in \Omega_S \tag{5.2}$$

In a two-stage multi-scenario problem, all branches representing uncertainty at the root (first stage decision) split at the second stage again, representing uncertainty between the second stage and the planing horizon (the leaf of the tree). Such a tree for a two-stage four-scenario case is shown in Figure 5.3a. This scenario tree can be decomposed into a tree without branches set of scenarios containing all individual scenarios in the set Ω_S, as is shown in Figure 5.3b. Decomposing a branched scenario tree into an unbranched multistage scenario tree means that the nodes that previously branched in the second stage exist multiple times in the decomposed unbranched multistage tree. This is indicated by the shaded areas around these nodes in the example shown in Figure 5.3. This relationship between these coupled nodes in the decomposed scenario tree needs to be taken into account when designing and applying algorithms to the decomposed tree. For example, when changes are made to the system state of such a coupled node in one scenario, these changes must be applied to the coupled nodes in the corresponding other scenario(s), potentially triggering secondary effects in the states of those other scenarios. Some authors call the decomposed scenario tree *simulated paths*, and the graph resulting from the fact that the decisions are coupled between some nodes in such simulated paths (as indicated with the shading in Figure 5.3b), *bundled simulated paths* (Hibiki, 2006).

As in the single-stage case, the weights σ_p^s of all n_s discrete scenarios, shown in Figure 5.3b must add up to 1 in each stage of the multistage problem, such that equation (5.3) holds. In the case of decomposed scenarios (simulated paths as shown in Figure 5.3b), scenario branches with the same original weights (i.e. the weights of the original branch in the scenario tree shown in Figure 5.3a) exist multiple times per period. Therefore, the summed weights of those multiple branches must be divided by the number of multiple branches introduced for one original branch. Likewise, if possibilistic multi-scenario planning is considered, all weights per stage must be equal as in equation (5.2) as well as their product per scenario must be equal, such that equation (5.4) holds. For $s \in \Omega_S$, where Ω_S is the set of all scenarios, n_s is the number of scenarios in set Ω_S. And for $p \in P$, where P is the set of all planning periods, n_p is the number of periods in set P

$$\sum_{s=1}^{n_s} \sigma_p^s = 1 \quad \forall s \in \Omega_S, \quad \forall p \in P \tag{5.3}$$



(a) two-stage four-scenario tree (b) two-stage four-scenario tree decomposed

Figure 5.3: Two-stage scenario tree and its decomposition

$$\prod_{p=1}^{n_p} \sigma_p^s = \frac{1}{n_s} \quad \forall s \in \Omega_S, \quad \forall p \in P \tag{5.4}$$

5.5 Solution methods for planning under uncertainty

As mentioned in Section 5.3, various solution methods for planning under uncertainty exist. This thesis is particularly concerned with long-term DNP and therefore the long-term uncertainties described previously. That is not to say that short-term uncertainties do not matter, indeed these can be integrated in the long-term planning problem, though are of relatively less impact on the overall problem. Here, short-term uncertainties such as load and DG stochasticity are considered to be accounted for in the model input, i.e. in the peak-load modelling.

In this thesis modelling of short-term uncertainties is not incorporated into the DNP problem. The focus is rather laid upon the long-term (deep) uncertainties which are considered to be modelled in scenarios. In the rest of this chapter, uncertainty is considered as modelled in scenario-trees. Scenario tree generation or uncertainty modelling in the broader sense is not part of this thesis and therefore considered as an external input to the proposed solution methods.

5.6 Single-stage multi-scenario distribution network planning

In this section, only one planning stage is considered, analogous to Chapter 3. In this single-stage multi-scenario planning approach, uncertainty is assumed to be sufficiently well modelled in the scenario tree that is provided as an input to the model.

5.6.1 Problem statement

In the following, a general problem formulation for single-stage multi-scenario DNP using conventional and non-conventional expansion technologies and solutions is presented. The single-stage DNP problem aims at identifying optimal investment decisions under uncertainty. Uncertainty is expressed in a scenario tree with n_s discrete branches, as described in Section 5.4. The expansion measures considered in the decisions are conventional (transformers and lines) and non-conventional (contracted flexibility) expansion measures.

5.6.2 Problem formulation

The objective function (OF) minimises the sum of discounted annuities of the investment and operational cost within the planning horizon, considering the uncertain variable states of all scenarios. Therefore, the optimal solution to the problem describes the least-cost expansion plan that is robust in all scenarios. The annuity represents an annual payment comprised of annual operational cost as well as an annual share of initial investment cost discounted and spread over the lifetime of a grid asset. Annuity calculations, as in equations (5.6-5.16) are used to make investments with different lifetime comparable and account for the value of those beyond the planning horizon.The binary decision variables contained in equations (5.12 - 5.16), represent investment decisions for transformers ($b_{br_{ij},tra}$) and lines ($b_{br_{ij},li}$) as well as contracting of flexibility ($b_{i,fl}$). The problem at hand is subject to multiple constraints, which are described in this Section below.

Mathematical problem formulation

In the following, the OF of the problem formulated above is described mathematically.

$$\min \quad \sum_{i=1}^{n} \frac{1}{(1+r)^i}(A(G) + A(F)) \tag{5.5}$$

where

$$A(G) = A^{inv}(G) + A^{op}(G) \tag{5.6}$$

$$A(F) = A^{op}(F) \tag{5.7}$$

$$A^{inv} = C^{inv}\,\alpha_{n,r} \tag{5.8}$$

$$A^{op} = C^{op}_{li,tot} + C^{op}_{tra,tot} + C^{op}_{fl,tot} \tag{5.9}$$

$$\alpha_{n,r} = \frac{1}{1 - \frac{1}{(1+r)^n}} \tag{5.10}$$

$$C^{inv} = C^{inv}_{li,tot} + C^{inv}_{tra,tot} \tag{5.11}$$

$$C^{op}_{li,tot} = \sum_{br_{ij}\in\Omega_{pl}} \sum_{li\in\Omega_{li}} b_{br_{ij,li}} \, C^{op}_{li} \, l_{br_{ij}} \tag{5.12}$$

$$C^{op}_{tra,tot} = \sum_{br_{ij}\in\Omega_{ds}} \sum_{tra\in\Omega_{tra}} b_{br_{ij,tra}} \, C^{op}_{tra} \tag{5.13}$$

$$C^{op}_{fl,tot} = \sum_{i\in\Omega_{dr}} \sum_{fl\in\Omega_{fl}} b_{i,fl} \, C^{op}_{fl} \tag{5.14}$$

$$C^{inv}_{li,tot} = \sum_{br_{ij}\in\Omega_{pl}} \sum_{li\in\Omega_{li}} b_{br_{ij,li}} \, C^{inv}_{li} \, l_{br_{ij}} \tag{5.15}$$

$$C^{inv}_{tra,tot} = \sum_{br_{ij}\in\Omega_{ds}} \sum_{tra\in\Omega_{tra}} b_{br_{ij,tra}} \, C^{inv}_{tra} \tag{5.16}$$

Investment and operational constraints

The OF is subject to the following investment and operational constraints.

$$h^s(G,F) \geq 0 \quad \forall s \in \Omega_S \tag{5.17}$$

Where h^s, shown in equation (5.17), is a generic function representing all investment and operational constraints in scenario s, respectively. These constraints are described in the following.

Within each scenario an upper boundary for investments in conventional expansion is limiting the number of parallel lines per power line branch as well as the number of parallel transformers per distribution substation branch.

As the multi-scenario single-stage DNP problem considers the peak-load in the network for a specific scenario as the relevant time slice for planning (Teichgraeber et al., 2022; Mateo, Gomez San Roman, et al., 2011), constraints describing operational limits of network assets have to be hold at these peak times. That means all common power flow equations must be solved and the following operational constraints be hold. The bounding constraint describing the permissible voltage at any node (5.18) and the inequality constraint describing the maximum current on any branch (5.19) for each scenario s are formulated.

$$V^{min}_i \leq V^s_i \leq V^{max}_i \quad \forall s \in S, \quad \forall i \in \Omega_b \tag{5.18}$$

$$I^s_{br_{ij}} \leq I^{max}_{br_{ij}} \quad \forall s \in S, \quad \forall ij \in \Omega_{br} \tag{5.19}$$

Additionally, full network connectivity (i.e. no unsupplied loads or network assets exist) is ensured at all times by a network connectivity constraint. This means that all nodes and consequently all loads are connected and none remains isolated. The network radiality constraint ensures that the network remains radial after new transformers and lines are added. Complying with all network operational constraints is ensured by power flow and graph analysis. As reliability is not studied in this thesis, only feasible solutions are considered. Therefore, the value of lost load is not part of the OF, shown in equation (5.5).

5.6.3 Solution method

A solution method is proposed below to solve the single-stage multi-scenario problem described in Section 5.6.2 using the single-stage DNP model described in Section 3.4. In the following possibilistic planning is considered, where no probabilities are assigned to the scenarios and reliability is not considered in the OF. Therefore, the solution method aims at obtaining a robust expansion solution considering the uncertainty in loads and/or DG, rather than an optimal one under the given uncertainty.

The uncertainties relevant to a DNP case are considered well represented in a scenario tree as input to the proposed model. This scenario tree, as shown in Figure 5.2, is decomposed into its n_s individual deterministic scenarios.

Each of the scenario branches, shown in the scenario tree in Figure 5.2, can be viewed as individual decomposed scenarios, exemplifying an alternative future materialising. Figure 5.4 shows any of the modelled scenarios realising, with one stage of robust expansion decision making, before the load growth is taking place. A feasible expansion decision consists of a first stage expansion plan $E_1 = G_1, F_1$ that is robust against all n_s scenarios.

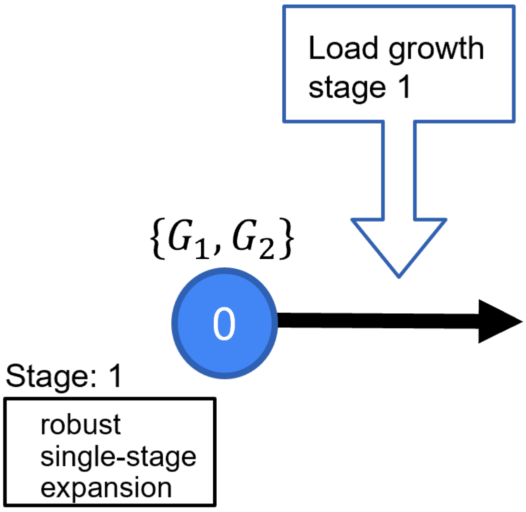


Figure 5.4: Single-stage scenario under load growth with robust first stage decision

The sequential solution method to obtain a robust expansion plan consists of three main steps as shown in Figure 5.5.

For the sake of simplicity, only two scenarios ($\Omega_S = \{s^A, s^B\}$) are considered in the following.

Step 1: Obtain initial candidate solutions:

In the first step, each of the scenarios was decomposed into its two individual scenarios (here $\Omega_S = \{s^A, s^B\}$). For each of these two scenarios, the deterministic single-stage DNP model is applied individually, yielding an optimal solution for each of the scenarios in Ω_S.

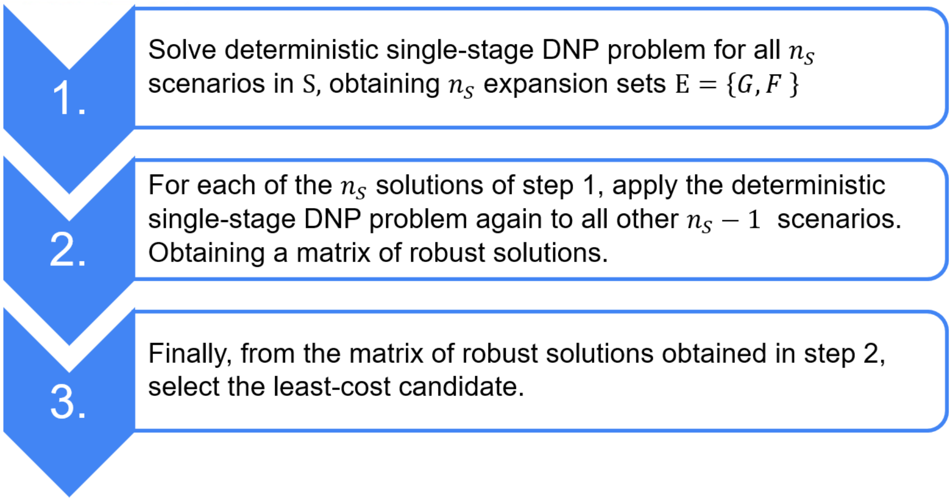


Figure 5.5: Generalised solution method for single-stage multi-scenario planning

Step 2: Make initial candidate solutions robust and generate solution matrix:

In the second step, the same DNP model is applied again, to each of the solutions obtained in step 1. Thus, obtaining two robust solutions (i.e. $2^2 - 2 = 2$ solutions). These Steps 1 and 2 are illustrated in Figure 5.6. This second step makes each solution obtained in the first step robust against the other scenario. In cases with more than two scenarios, the process of making the initial solution per scenario robust against the other n_s scenarios must be repeated against all respective other scenarios exactly $n_s - 1$ times, obtaining $n_s^2 - n_s$ solutions. The reason that this step of making expansion solutions robust against all scenarios is necessary, as long as it can not be safely assumed that one scenario is covering the load growth of a given other scenario. Such a case would exist if e.g. scenario B contains all loads as scenario A, plus additional loads or scaled loads, no DG and radial network structure. In this case the expansion solution for scenario B is naturally robust against the scenario A and one step of making expansion solution B robust against scenario A is obsolete. Though often this can not be assumed as loads could be distributed randomly in each scenario or DG could be present can alter the power flows in the network significantly.

The previously obtained solutions can then be visualised in a matrix as shown in Figure 5.7. Here, the columns s^A and s^B express the realisation of one of the two scenarios still uncertain at the time of the investment decision. The rows ($A \rightarrow B$) and ($B \rightarrow A$) show the order of creation of the robust solution (i.e. as in step 2 described above). In this table, the individual solutions are expressed in terms of their OF value, where $\{G^A, F^A\}$ and $\{G^B, F^B\}$ are the sets of conventional expansion measures (G^A, G^B) and contracted flexibility (F^A, F^B) chosen for the initial optimisation for scenario A and B, respectively, in step 1 of the methodology described above. The expansion sets $\{G^A*, F^A*\}$ and $\{G^B*, F^B*\}$ are the sets obtained in the second step of the methodology, when the expansion solutions obtained in the first step are made robust against the respective other scenario.

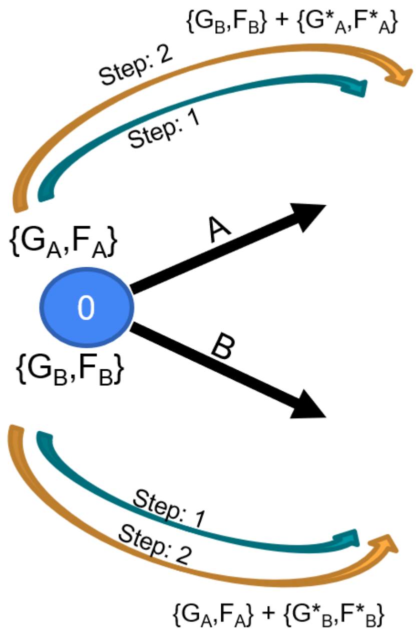


Figure 5.6: Process to obtain two robust solutions for single-stage DNP with scenarios A and B

Step 3: Select least-cost robust solution candidate:

Finally, in the third and last step of the solution method, the least-cost candidate among the solutions of the matrix shown in Figure 5.7 can be selected as the optimal solution robust to the modelled uncertainty. It is to be noted that the solutions in both columns are identical per row as long as the OF value is not influenced by operational decision making. Such could be the case if the actual activation of contracted flexibility in short-term planning and operational time-frames affects the cost considered in the OF.

For better illustration the solution method is described using only two distinct scenarios (i.e. $|\Omega_S| = n_s = 2$), that is the cardinality of the set Ω_S is 2. As explained earlier, this method can easily be generalised to cover more scenarios. Though, the size of the candidate solution matrix shown in Figure 5.7 grows quadratically (i.e. $n_s^2 - n_s$), with the number of distinct scenarios n_s in Ω_S.

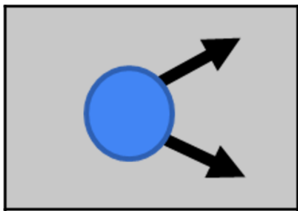
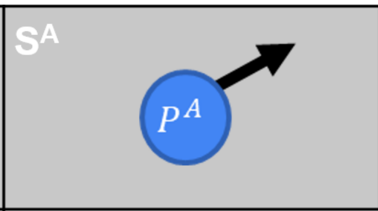
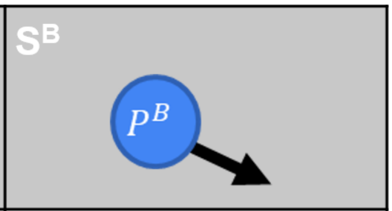
	S^A 	S^B 
$A \to B$: $P^{A,B}$: $\{G^A, F^A\}$ $+\{G^{B*}, F^{B*}\}$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i} \big(A(G^A) + A(G^{B*}) + A(F^A) + A(F^{B*})\big)$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i} \big(A(G^A) + A(G^{B*}) + A(F^A) + A(F^{B*})\big)$
$B \to A$: $P^{B,A}$: $\{G^B, F^B\}$ $+\{G^{A*}, F^{A*}\}$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i} \big(A(G^B) + A(G^{A*}) + A(F^B) + A(F^{A*})\big)$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i} \big(A(G^B) + A(G^{A*}) + A(F^B) + A(F^{A*})\big)$

Figure 5.7: Matrix of robust solutions for single-stage DNP with scenarios A and B

5.7 Multistage multi-scenario distribution network planning

In this section, multistage DNP under uncertainty is considered, analogous to Chapter 4. To simplify the presentation of the problem and solution approach only two stages are considered. In the resulting two-stage multi-scenario planning approach, uncertainty is assumed to be sufficiently well modelled in the scenario tree that is provided as an input to the model.

5.7.1 Problem statement

In the following, a general problem formulation for multi-scenario two-stage DNP using conventional and non-conventional expansion technologies and solutions is presented. The two-stage multi-scenario DNP problem aims to identify optimal investment decisions under uncertainty, expressed over two stages within the planning horizon. The expansion measures considered in the decisions are conventional (transformers and lines) and non-conventional (contracted flexibility) expansion measures. Uncertainty is expressed in a scenario tree containing all possible realisations of the random variables considered. A single scenario describes a distinct path from the root to a leaf of the tree, passing both stages of the two stage problem. As the long-term uncertainty is realising over time and investment decisions have to be made consecutively, the objective is to identify a policy tree T. The tree specifies a decision to be taken at each stage t_p, depending on the realisation of the random variables in the previous stage. Based on the expansion decisions in the first stage and the realisation of some of the uncertainty in the second stage, the policy tree offers the possibility of making some recourse decisions, partially undoing the decisions made in the first stage that turn out to be sub-optimal in the second stage. In the present problem, the recourse action is represented by the contracting of flexibility, which is assumed to be contractable for a period equal to the planning periods, as well as further investments in conventional network expansion measures. This means that while the annuities for the transformer and line investments made in the first stage must also be paid in the second stage, the annuities associated with the flexibility contracts depend on the actual need for flexibility in the second stage decision. Planning over two periods has been chosen, as it allows to better observe the effects of possible network investment deferrals and the role that flexibility can play in this. It also helps to better understand the modelling of uncertainty in multi-scenario analysis. The two-stage model is relatively easily generalisable to a multistage model. In Appendix B.1, the model for two-stage DNP under uncertainty presented in this chapter is generalised. And in Appendix B.2, this two-stage generalisation is extended to a multistage multi-scenario model, including the generalised multistage multi-scenario tree shown in Figure B.1.

5.7.2 Problem formulation

The OF minimises the sum of discounted annuities of the investment and operational cost of both planning periods. Where the value of the second term (therefore stage) of the OF depends on the decisions made in the first term (stage), on the weighting factor σ^s of the respective scenario s as well as on the constraints in the second stage, represented by equation (5.33). Also, for the second term of the objective function one value exists for each of the n_s scenarios, that is weighted (σ^s) into the expected value of the OF second stage term. The second term of the OF is also commonly referred to as *recourse function* or *expected recourse function*. The annuity represents an annual payment comprised of annual operational cost as well as an annual share of initial investment cost discounted and spread over the lifetime of an asset. Annuity calculations, as in equations (5.21-5.31) are used to make investments with different lifetime comparable and account for the value of those beyond the planning horizon.

The binary decision variables contained in equations (5.27 - 5.31), represent investment decisions for transformers ($b_{br_{ij},tra}$) and lines ($b_{br_{ij},li}$) as well as contracting of flexibility ($b_{i,fl}$). The fact that flexibility contracted for the first period does not necessarily have to be contracted for the second period, depending on how the future unfolds, represents an added value of flexibility in multistage multi-scenario DNP. The problem at hand is subject to multiple constraints, which are described in Section 5.7.2.

Mathematical problem formulation

In the following, the OF of the problem formulated above is described mathematically.

$$\begin{aligned}\min \quad & \sum_{i=1}^{n_{p1}} \frac{1}{(1+r)^i}(A(G_{p1}) + A(F_{p1})) \\ & + \sum_{s=0}^{n_s}\left(\sigma^s * \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}(A(G_{p1}) + A(G^s_{p2}) + A(F^s_{p2}))\right)\end{aligned} \tag{5.20}$$

where

$$A(G) = A^{inv}(G) + A^{op}(G) \tag{5.21}$$

$$A(F) = A^{op}(F) \tag{5.22}$$

$$A^{inv} = C^{inv}\, \alpha_{n,r} \tag{5.23}$$

$$A^{op} = C^{op}_{li,tot} + C^{op}_{tra,tot} + C^{op}_{fl,tot} \tag{5.24}$$

$$\alpha_{n,r} = \frac{1}{1 - \frac{1}{(1+r)^n}} \tag{5.25}$$

$$C^{inv} = C^{inv}_{li,tot} + C^{inv}_{tra,tot} \tag{5.26}$$

$$C^{op}_{li,tot} = \sum_{br_{ij} \in \Omega_{p}l} \sum_{li \in \Omega_{li}} b_{br_{ij,li}}\, C^{op}_{li}\, l_{br_{ij}} \tag{5.27}$$

$$C^{op}_{tra,tot} = \sum_{br_{ij} \in \Omega_{ds}} \sum_{tra \in \Omega_{tra}} b_{br_{ij,tra}}\, C^{op}_{tra} \tag{5.28}$$

$$C^{op}_{fl,tot} = \sum_{i \in \Omega_{dr}} \sum_{fl \in \Omega_{fl}} b_{i,fl}\, C^{op}_{fl} \tag{5.29}$$

$$C^{inv}_{li,tot} = \sum_{br_{ij} \in \Omega_{pl}} \sum_{li \in \Omega_{li}} b_{br_{ij,li}}\, C^{inv}_{li}\, l_{br_{ij}} \tag{5.30}$$

$$C^{inv}_{tra,tot} = \sum_{br_{ij} \in \Omega_{ds}} \sum_{tra \in \Omega_{tra}} b_{br_{ij,tra}}\, C^{inv}_{tra} \tag{5.31}$$

Investment and operational constraints

The OF is subject to the following investment and operational constraints.

$$h_1^s(G_{p1}, F_{p1}) \geq 0 \quad \forall s \in \Omega_S \tag{5.32}$$

$$h_2^s(G_{p1}, G^s_{p2}, F^s_{p2}) \geq 0 \quad \forall s \in \Omega_S \tag{5.33}$$

Where h_1 and h_2, shown in equations (5.32) and (5.33), are generic functions representing all investment and operational constraints in period 1 and period 2, respectively. These constraints are described in the following.

Within a single planning period, an upper boundary for investments in conventional expansion is limiting the number of parallel lines per power line branch as well as the number of parallel transformers per distribution substation branch. Between the individual planning periods, constraints ensure that investments in conventional expansions made in the first period (i.e G_{p1}) are also accounted for, together with the additional investments in the second period (i.e G_{p1} and

G_{p2}). This is due to the fact that grid assets, such as lines and transformers, once installed are usually not removed until the end of their useful life. On the contrary, flexibility can be contracted in shorter intervals, depending on the short-term planning of the distribution system operator. Therefore, annuities of flexibility (i.e. F_{p1}, F_{p2}) are only accounted for in the planning period that the flexibility is also contracted, as shown in equation (5.20).

As the multi-scenario multistage DNP problem considers the peak-load in the network as the relevant time slice for planning (Teichgraeber et al., 2022; Mateo, Gomez San Roman, et al., 2011), constraints describing operational limits of network assets have to be hold at these peak times for each stage in each of the scenarios. That means all common power flow equations must be solved and the following operational constraints be hold. The bounding constraint describing the permissible voltage at any node (5.34) and the inequality constraint describing the maximum current on any branch (5.35) for each scenario s and each period p are formulated.

$$V_i^{min} \leq V_{i,p}^s \leq V_i^{max} \quad \forall s \in S, \quad \forall i \in \Omega_b \tag{5.34}$$

$$I_{br_{ij},p}^s \leq I_{br_{ij}}^{max} \quad \forall s \in S, \quad \forall ij \in \Omega_{br} \tag{5.35}$$

Additionally, full network connectivity (i.e. no unsupplied loads or network assets exist) is ensured at all times by a network connectivity constraint. This means that all nodes and consequently all loads are connected and none remains isolated. The network radiality constraint ensures that the network remains radial after new transformers and lines are added. Complying with all network operational constraints is ensured by power flow and graph analysis. As reliability is not studied in this thesis, only feasible solutions are considered. Therefore, the value of lost load is not part of the OF, shown in equation (5.20).

5.7.3 Solution method

In the following, a solution method is proposed to solve the two-stage multi-scenario problem described in Section 5.7.2 and to obtain a policy tree T as a solution. As in the solution method proposed in Section 5.6.3, the following considers possibilistic planning. No probabilities are assigned to the scenarios and reliability is not considered in the OF. Therefore, the solution method aims at obtaining a policy tree with robust expansion solutions, taking into account the uncertainty in loads and/or DG, rather than an optimal one under the given uncertainty.

The uncertainties relevant to a DNP case are considered well represented in a scenario tree as input to the proposed model. This scenario tree is decomposed into its n_s individual deterministic scenarios. Here, only two scenarios with two stages each are considered in order to better explain the solution method. Therefore, the resulting decomposed scenario tree is shown in Figure 5.8. The red arrows describe the load growth in the second stage, which can be omitted for simpler illustration.

Each of the scenario branches, shown in the scenario tree in Figure 5.8, can be viewed as individual decomposed scenarios, exemplifying an alternative future materialising. Figure 5.9 shows any of the modelled scenarios realising, with two stages of expansion decision making, each before the respective load growth is taking place. A feasible expansion policy consists of a robust first stage expansion plan $E_1 = G_1, F_1$ and n_s expansion plans for the second stage $E_2 = G_2^s, F_2^s$.

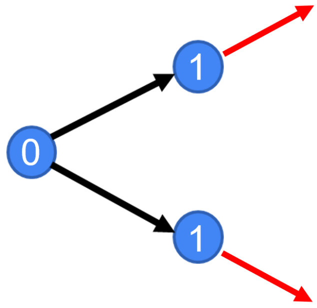


Figure 5.8: Two stage, two scenario tree, highlighting omitted branch notation

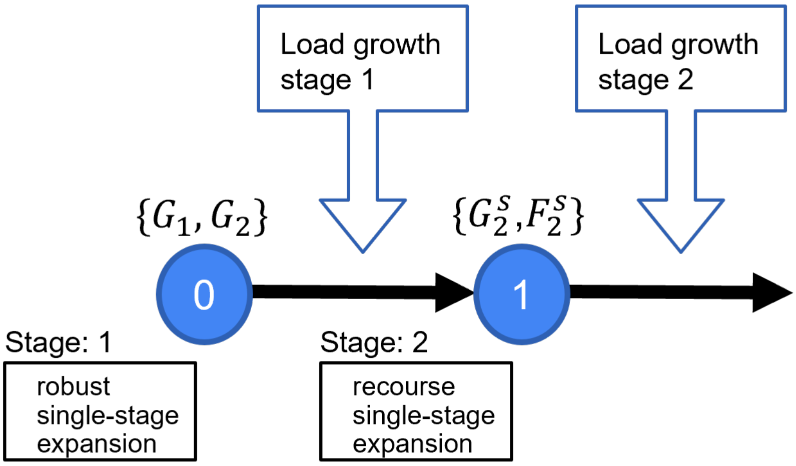


Figure 5.9: Two-stage scenario under load growth, robust first stage decision and second stage recourse decision

The sequential solution method to obtain such a policy tree consists of four main steps as shown in Figure 5.10. For the sake of simplicity, only two scenarios ($\Omega_S = \{s^A, s^B\}$) are considered here.

Step 1: Obtain initial candidate solutions:

In the first step, each of the scenarios was decomposed into two individual scenarios (here $\Omega_S = \{s^A, s^B\}$). For each of the scenarios in Ω_S, the deterministic two-stage DNP problem is solved applying the methodology described in Section 4.4, yielding an optimal solution for each of the two-stage scenarios in Ω_S. For scenario A, the resulting expansion sets are $\{\{G_1^A, F_1^A\} + \{G_2^A, F_2^A\}\}$, for scenario B they are $\{\{G_1^B, F_1^B\} + \{G_2^B, F_2^B\}\}$.

Step 2: Make initial candidate solutions robust for the first stage:

In the second step, the deterministic single-stage DNP model described in Section 3.4 is applied, to each of the solutions obtained in step 1 for each of the respective other first stages. Thus, obtaining 2 solutions robust in the first stage. For the case of making A robust against B ($A \rightarrow B$), this set

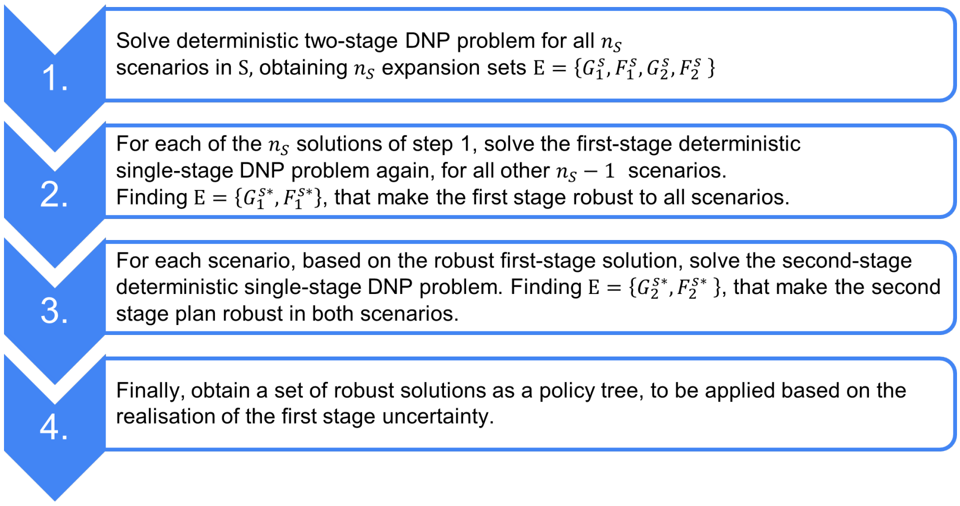


Figure 5.10: Generalised solution method for two-stage multi-scenario planning

is $P_1 = \{\{G_1^A, F_1^A\} + \{G_1^{B*}, F_1^{B*}\}\}$. And for the case of making B robust against A and $(B \rightarrow A)$, this set is $P_1 = \{\{G_1^B, F_1^B\} + \{G_1^{A*}, F_1^{A*}\}\}$.

In cases with more than two scenarios, the process of making the initial solution per scenario robust against the other n_s scenarios must be repeated against all respective other scenarios exactly $n_s - 1$ times, obtaining $n_s^2 - n_s$ solutions. The reason that this step of making expansion solutions robust against all scenarios is necessary, as long as it can not be safely assumed that one scenario is covering the load growth of a given other scenario. An example for such a case is given in the description of step 3 of the solution method for single-stage multi-scenario DNP presented in Section 5.6.3.

Step 3: Create expansion policy options for the second stage and generate solution matrix:

In the third step, for each of the scenarios (here $\{s^A, s^B\}$) the same deterministic single-stage DNP model as in step 2 is applied for the second stage of each scenario, using each of the robust solutions obtained in step 2 as an input $(P_1 : A \rightarrow B; P_1 : B \rightarrow A)$. Therefore obtaining the second stage expansion options for both of the two scenarios ($\{G_2^{A*}, F_2^{A*}\}$ and $\{G_2^{B*}, F_2^{B*}\}$) that make the second stage expansion robust, based on the realisation of the uncertainty in stage 1 (i.e. whether scenario s^A or scenario s^B materialises). In this case only one second stage scenario per first stage scenario branch exists, therefore only one solution per scenario has to be created. In cases with more than two scenarios in the second stage, the process of making the robust first stage solutions robust against the other n_s scenarios must be repeated against all respective other scenarios exactly $n_s - 1$ times for each branch of the scenario tree, obtaining $n_s^2 - n_s$ solutions for each of the first stage branches. In case of two first stage branches and two second stage branches as illustrated in Figure 5.3a, step 3 would lead to $2 * (2^2 - 2) = 4$ solutions for the second stage or two solutions per first stage branch.

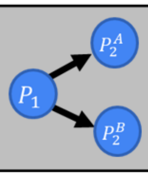
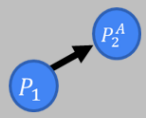
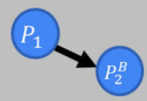
	$\mathbf{S^A}$ 	$\mathbf{S^B}$ 
A→B: P_1: $\{G_1^A, F_1^A\}$ $+ \{G_1^B*, F_1^B*\}$ P_2^A: $\{G_2^A, F_2^A\}$ P_2^B: $\{G_2^{B*}, F_2^{B*}\}$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(F_{P1})\right)$ $+ \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(G_2^A)\right.$ $\left.+ A(F_2^A)\right)$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(F_{P1})\right)$ $+ \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(G_2^B*)\right.$ $\left.+ A(F_2^B*)\right)$
B→A: P_1: $\{G_1^B, F_1^B\}$ $+\{G_1^{A*}, F_1^{A*}\}$ P_2^A: $\{G_2^{A*}, F_2^{A*}\}$ P_2^B: $\{G_2^B, F_2^B\}$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(F_{P1})\right)$ $+ \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(G_2^A*)\right.$ $\left.+ A(F_2^{A*})\right)$	$\sum_{0}^{n_{p1}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(F_{P1})\right)$ $+ \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}\left(A(G_{P1}) + A(G_2^B)\right.$ $\left.+ A(F_2^B)\right)$

Figure 5.11: Matrix of robust solutions for two-stage DNP with scenarios A and B, as policy options

The previously obtained solutions can then be visualised in a matrix as shown in Figure 5.11. Here, the columns s^A and s^B express the realisation of one of the two scenarios still uncertain at the time of the investment decision. The rows $(A \rightarrow B)$ and $(B \rightarrow A)$ show the order of creation of the robust solution (i.e. as in step 2 and 3 described above). In this table, the individual solutions are expressed in terms of their OF value. There $\{G_{P1}, F_{P1}\}$ include the expansion sets $E = \{\{G_1^A, F_1^A\} \cup \{G_1^{B*}, F_1^{B*}\}\}$ and $E = \{\{G_1^B, F_1^B\} \cup \{G_1^{A*}, F_1^{A*}\}\}$ respectively, that make the first stage expansion robust for the first period.

Step 4: Select least-cost robust solution candidate:

Finally, in the fourth and last step, the least-cost candidate among the solutions of the matrix shown in Figure 5.11 can be selected as the preferred solution robust to the modelled uncertainty. These solutions represent a policy tree T as a solution to the two-stage, two-scenario DNP problem, where the expansion decision for the first stage (*here and now*) is made robustly and expansion policies exist for the second stage decisions. Those policies can then be executed depending on how the uncertainty realises, that is whether scenario A or scenario B is happening.

For better illustration the solution method is described using only two distinct scenarios (i.e. $|\Omega_S| = n_s = 2$), that is the cardinality of the set Ω_S is 2. As explained earlier, this method can easily be generalised to cover more scenarios and stages. Though, the size of the candidate solution matrix shown in Figure 5.11 grows as $(n_s^2 - n_s)$, with the number of distinct scenarios n_s in Ω_S.

5.8 Case study

This section presents a case study of multi-scenario, multistage DNP using flexibility contracting as an alternative to conventional network expansion measures. The assumptions and their modelling for the case study are described below, combining the modelling of the initial network, the modelling of two different load growth scenarios, each with two planning phases, and the modelling of conventional and non-conventional network expansion. In this case study, a risk-averse attitude of the planner is assumed. This means that any expansion plan must ensure that all consumers are supplied and all operational constraints are met, regardless of the realisation of uncertainty (i.e. for all scenarios). Therefore, robust DNP under uncertainty is considered.

5.8.1 General modelling assumptions

The network operational constraints are implemented as follows. The voltage limit is set to +/- 10 % of the nominal voltage. The current capacity limit is set to 100 % of each asset's nameplate capacity.

The discounting rate used in the economic evaluation of the investment decisions is based on the Weighted Average Cost of Capital (WACC) and is set to 6 %. Based on Spanish regulation (Comisión Nacional de los Mercados y la Competencia, 2019) the regulatory expected lifetime of transformers and power lines is set to 40 years. The investment and maintenance cost for conventional network expansion is based on State Gazette no. 297 (Ministerio de Industria, Energía y Turismo, 2015).

Contracted flexibility is formulated as an estimated annual capacity price, that indirectly entails the cost of energy used during the activation of the contracted flexibility. Flexibility contracting costs are set to 10 €/kW per year. This value has been selected from a range given in (UKPN, 2021; SP Energy Networks, 2022). In contrast to previous case studies in this thesis, additional considerations regarding flexibility contracting and usage are taken. As previously considered, contracted flexibility is payed for annually. Though here, as the need for actually using (i.e. activating) flexibility depends on the realisation of the uncertain future, a part of the flexibility contracting cost is only due if actually activated by the DSO in a given scenario. That is, if flexibility is contracted for a planning period, but in a materialising scenario that flexibility does not need to be activated only 50 % of the flexibility cost are to be payed for by the DSO to the flexibility provider.

5.8.2 Initial network

The initial network used as input to this model is created applying the Greenfield RNM (Mateo, Gomez San Roman, et al., 2011; Mateo, Prettico, et al., 2018). The Greenfield RNM is able to create large-scale realistic network models based on high-level demographic data, electricity consumption data and geographic data from OpenStreetMap.

The network model shown in Figure 5.12 is an MV/LV-feeder located in the North-East corner of a realistic network model of Albacete, Spain. The feeder contains 5 MV/LV distribution substations with respective LV feeders. The two voltage levels are rated at 20 kV (MV) with 5 buses and 1.196 km of power lines as well as 0.4 kV (LV) with 91 buses and power lines of 2.718 km in length. The total nameplate capacity of the 5 transformers in the 5 DS is 2.450 MVA. The 86 loads in the initial network create a peak demand of 1.565 MW and 0.467 Mvar. The time slice relevant for peak-load expansion planning is estimated using simultaneity factors applied to individual consumer peaks, as described in (Mateo, Gomez San Roman, et al., 2011).

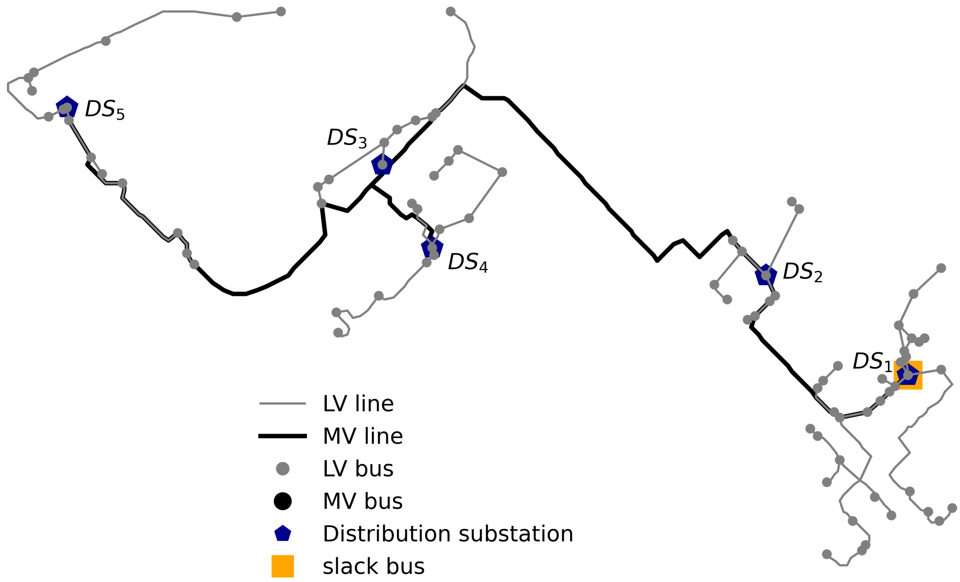


Figure 5.12: Plot of MV/LV feeder before expansion

5.8.3 Load growth scenario modelling

Two scenarios with two stages each are considered. Both scenarios consider load growth due to electrification of the transport sector, being distinct only by the magnitude of load growth. In both scenarios, three types of EVC are randomly added to the LV network.

To better illustrate the value of flexibility contracting in DNP under uncertainty, the load growth assumptions are simplified. That is only the first stage contains uncertainty of load growth, while the load stagnates in the second stage of both scenarios. The resulting scenario tree is illustrated in Figure 5.13.

In the first stage of scenario s^A (s^A_{p1}), 105 EVC with a rating of 3.7 kW and 8 rated at 11 kW are added, resulting in a peak-load growth of 0.477 MW or 30.45 %. The second stage of scenario s^A (s^A_{p2}) contains no load growth. In the first stage of scenario s^B (S^B_{p1}), all EVCs as in scenario s^A are added, plus another 105 EVCs with a rating of 3.7 kW, 26 EVCs rated at 11 kW as well as 5 rated at 22 kW. This results in an addition of overall 210 EVCs with a rating of 3.7 kW, 34 EVCs rated at 11 kW as well as 5 rated at 22 kW, resulting in a peak-load growth of 1.261 MW or 80.58 %. The second stage of scenario s^B (S^B_{p2}) contains no load growth. The first period constitutes 5 years and the second period constitutes 15 years, totalling an overall planning horizon of 20 years.

5.8.4 Network expansion modelling, conventional measures

The network expansion options are classified as conventional (transformer and power line expansion) and non-conventional (flexibility contracting) options. Transformer expansion options

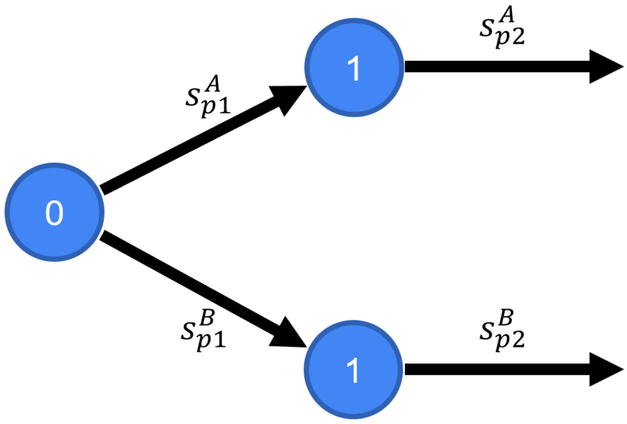


Figure 5.13: Two-stage scenario tree with two branches

comprise the installation of parallel transformers as well as the exchange (upgrade) of transformers with a bigger capacity, or a combination of parallel addition and exchange. In conformity with the State Gazette no. 297 of 12 December 2015 (Ministerio de Industria, Energía y Turismo, 2015), four standard capacities of three-phase transformers are available for expansion, namely 250 kVA, 400 kVA, 630 kVA and 1000 kVA. The upper boundary describing the maximum parallel transformers per distribution substation branch is set to 3 in this case study. Power line expansion options are modelled by parallel additions of power lines, of equal capacity as the existing line, on the respective power line branches. The constraint describing the maximum parallel additions of lines per power line branch is set to 3 in this case study.

5.8.5 Network expansion modelling, non-conventional measures

In this case study, flexibility contracting as a non-conventional expansion option is modelled as follows. Loads with contracted flexibility reduce their peak load contribution capacity by 50 %. Half of the randomly selected initial network loads and all additional EVC loads are assumed to be contractable. This gives a total potential peak reduction of 0.619 MW in scenario s^A and 1.011 MW in scenario s^B. Flexibility is activated per bus, i.e. when flexibility is activated on a specific bus of the network, all available flexibility contracts connected to that bus are activated.

5.9 Results and discussion

The results of the robust two-stage, two-scenario planning approach applying conventional expansion measures as well as non-conventional expansion utilising flexibility contracting are presented in the following. Firstly, two expansion plans for both individual scenarios are obtained based on the multistage DNP methodology presented in Section 4.4. Then, applying a robust solution is selected and a policy tree is defined, allowing for adoptions in the second decision-making stage. The possible impact of flexibility in this stage, based on the materialised uncertainty is consequently presented.

5.9.1 Obtaining initial multistage solutions

In line with step 1 of the solution method presented in Section 5.7.3, the pseudo-dynamic forward fill-in approach for multistage DNP, as presented in Section 4.4 is applied for two scenarios (i.e. s^A and s^B). This results in the two expansion plans presented in Table 5.1, showing the network evolution in the two cases over both planning periods. In addition, Table 5.2 shows the respective evolution of the NPV of the total costs.

Plan A:

In scenario A, period 1 (S^A_{p1}), the LV line circuitry is expanded by 0.103 km, and the transformer capacity is expanded by 400 kVA, by adding one transformer in parallel to an existing one, as shown in Table 5.3. In this table, the $DS_1 - DS_5$ are the distribution substations, where at least one transformer must be installed. Additionally, 67.53 kW of flexibility is contracted as a non-conventional expansion measure. The resulting network, with the expansions of the first period highlighted in red, is shown in Figure 5.14. In period 2 of scenario A (S^A_{p2}), no load growth is taking place, therefore no conventional expansion or flexibility contracting is taking place. The flexibility contracted in period 1 is contracted again in period 2 to cover the same load. As shown in Table 5.2, the cost for the individual periods results in the NPV of the total cost of 49,141 € for all planning periods.

Plan B:

In plan B for scenario B, period 1 (S^B_{p1}), the LV line circuitry is expanded by 0.375 km, one new transformer is installed in parallel and 4 transformers are upgraded (exchanged), adding a capacity of 1,470 kVA, as shown in Table 5.3. In this table, the $DS_1 - DS_5$ are the distribution substations, where at least one transformer must be installed. Also, 56.21 kW of flexibility is contracted in this period, as a non-conventional expansion measure. The resulting network, with the expansions of the first period highlighted in red, is shown in Figure 5.15. In period 2 of scenario B (S^B_{p2}), no load growth is taking place, therefore no conventional expansion or flexibility contracting is taking place. The flexibility contracted in period 1 is contracted again in period 1 to cover the same load. In this case, as shown in Table 5.2, the cost for the individual periods results in the NPV of the total cost of 205,850 € for all planning periods. Which is 319 % higher than the cost for expansion plan A.

5.9.2 Obtaining the robust expansion plan

Based on the methodology presented in Section5.7.3, after obtaining the initial solutions step 2 and 3 ask to make those solutions robust against each other. In the following it is explained why in this case study these steps can be significantly simplified.

As described in Section 5.8.3, the load growth in scenario B contains all the load growth in scenario A plus additional load growth. Therefore, the network expanded for scenario B, as described previously, is also robust against scenario A. This holds due to two conditions, firstly the network is radial and secondly there is no DG modelled in this case study. Also, there is no load growth in the second stage of either scenario. For this illustrative case study it is therefore also not

		scenario A		scenario B	
	initial year	period 1	period 2	period 1	period 2
Loads					
$P_{load,pre}$ $[MW]$	1.555	2.032	2.032	2,816	2,816
$P_{flex,act}$ $[MW]$	0	0.068	0.068	0.056	0.056
$P_{load,tot}$ $[MW]$	1.555	1.964	1.964	2.760	2.760
Transformers					
count	5	6	6	6	6
capacity $[MVA]$	2.45	2.85	2.85	3.92	3.92
Power lines					
MV circuitry $[km]$	1.196	1.196	1.196	1.196	1.196
LV circuitry $[km]$	2.718	2.821	2.821	3.093	3.093

Table 5.1: Results of two-stage planning with flexibility contracting for scenario A and B.

	scenario A			scenario B		
	period 1	period 2	total	period 1	period 2	total
NPV:	18,047	31,094	49,141	75.599	130,251	205.850
of which:						
Transformers	13,523	23,298	36,821	67,113	115,630	182,743
Power lines	1,680	2,895	4,575	6,118	10,541	16,659
Flexibility	2,844	4,901	7,745	2,368	4,080	6,448

Table 5.2: NPV of total cost [€] with flexibility contracting in scenario A and B.

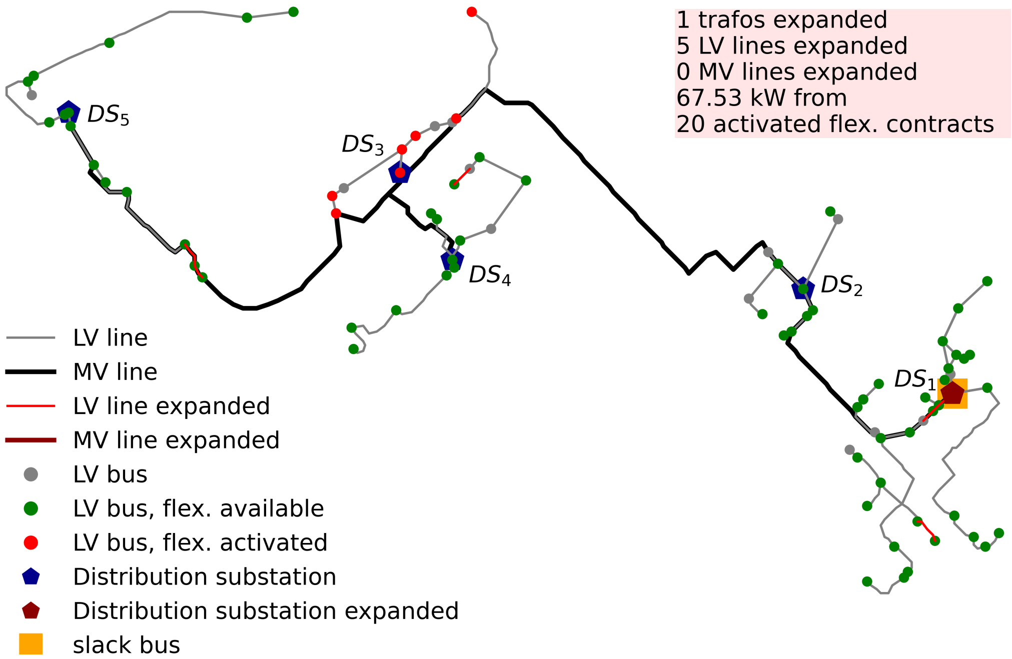


Figure 5.14: Network expansion plot with flexibility activation, scenario A

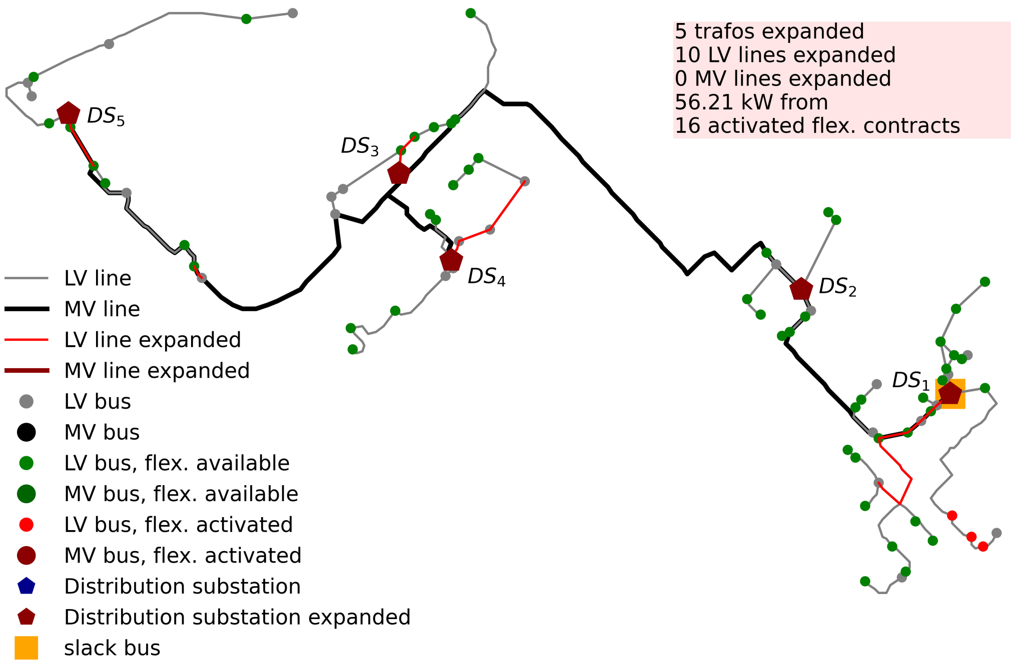


Figure 5.15: Network expansion plot with flexibility activation, scenario B

transformers [kVA] at distribution substation	DS_1	DS_2	DS_3	DS_4	DS_5
initial year	1000	400	250	400	400
scenario A, period 1	1000 400	400	250	400	400
scenario A, period 2	1000 400	400	250	400	400
scenario B, period 1	1000 400	630	400	630	630
scenario B, period 2	1000 400	630	400	630	630

Table 5.3: Evolution of installed transformers [kVA] at distribution substations, scenario A and B

necessary to make the expansion plan for scenario A robust against scenario B, as opposed to the methodology presented in Section 5.7.3. This robust plan is considered in the following section to explore the two-stage expansion policy for both scenarios.

5.9.3 Comparison of expansion policies

The previous section presented two expansion plans for the two scenarios A and B. Plan B was identified as the robust expansion plan, as the network expanded according to this plan is capable of accommodating the load growth of both scenarios without violating any operational constraints. Based on the planner's risk aversion, it is assumed that the robust plan (Plan B) will be implemented. What follows is an analysis of what happens in the second stage of the decision, based on the uncertainty that has already been realised. That is, what options does the decision maker have in the second stage after the uncertainty has been resolved in either Scenario A or Scenario B. As there is no load growth happening in the second stage of either scenario, conventional network investment decisions will only have to be made in the first stage. Though, as flexibility is contracted in the same interval as the planing period, the second stage decisions include the re-contracting of flexibility. In multistage stochastic optimisation, such later stage decisions are known as recourse decisions.

The NPV of the total expansion costs and by category for the robust Plan B under Scenarios A and B are shown in Table 5.4. The total load and network data from the initial year through period 1 and 2 for scenarios A and B is shown in Table 5.1.

Scenario A materialises:

If scenario A materialises, the expansion measures contained in plan B cover the load growth of scenario A, as plan B is robust to scenario A. As described in Section 5.8.3, in the second stage decision there is no uncertainty and no further load growth is assumed. As in the previous case, the conventional network elements (i.e. transformers and lines) are present in the second stage. Though the decision to contract flexibility must be revised to efficiently cover the load of scenario A, period 2 (S^A_{p2}). As shown in Table 5.5, the total load in both periods of scenario A is 2.031 MW, which does not include any reduction due to flexibility activation as due to the lower load scenario A materialising. That is, the operational activation of the flexibility is not needed, even though 50 % of the the flexibility contracted in period 1 needs to be paid for, as shown in Table 5.4. The cost for the individual periods results in the NPV of the total cost of 200.586 € for all planning periods. Therefore, in this case study the usage of flexibility contracting at a cost of 10 €/kW per year results in total cost savings of 5,264 €or 2.56 % over the planning horizon of 20 years.

Scenario B materialises:

If Scenario B materialises, the expansion measures included in Plan B cover the load growth of scenario B. As described in Section 5.8.3, in the second stage decision there is no uncertainty and no further load growth is assumed. Therefore, to meet the same load, the same network elements (i.e. transformers and lines) must be in place and the same flexibility must be contracted. Due to the long lifetime of conventional network elements, the expansion measures of the first period are present in the second period. Flexibility contracted in the first period must be contracted again for the second period. These cost for the individual periods results in the NPV of the total cost of 205.850 € over the planning horizon of 20 years.

	plan B under scenario A			plan B under scenario B		
	period 1	period 2	total	period 1	period 2	total
NPV:	74,415	126,171	200,586	75.599	130,251	205.850
of which:						
Transformers	67,113	115,630	182,743	67,113	115,630	182,743
Power lines	6,118	10,541	16,659	6,118	10,541	16,659
Flexibility	1,184	0	1,184	2,368	4,080	6,448

Table 5.4: NPV of total cost [€] with flexibility contracting for robust plan B under scenarios A and B.

5.9.4 General findings

The application of the multistage model for a two-stage DNP, including flexibility contracting as an non-conventional expansion measure, has shown an interesting effect that is valuable for supporting investment decisions under significant load growth uncertainty. Selecting the robust ex-

		plan B under scenario A		plan B under scenario B	
	initial year	period 1	period 2	period 1	period 2
Loads					
$P_{load,pre}$ $[MW]$	1.555	2.032	2.032	2,816	2,816
$P_{flex,act}$ $[MW]$	0	0	0	0.056	0.056
$P_{load,tot}$ $[MW]$	1.555	2.032	2.032	2.760	2.760
Transformers					
count	5	6	6	6	6
capacity $[MVA]$	2.45	3.92	3.92	3.92	3.92
Power lines					
MV circuitry $[km]$	1.196	1.196	1.196	1.196	1.196
LV circuitry $[km]$	2.718	3.093	3.093	3.093	3.093

Table 5.5: Results of two-stage planning with flexibility contracting for robust plan B under scenarios A and B.

pansion plan that can cover both load growth scenarios of the decision without risking loss of load or constraint violations inevitably leads to significantly higher expansion costs, especially in this case study where the expansion costs are about four times higher than in the lower load growth scenario. Due to the uncertainty in load growth and the significant difference between the two scenarios in this case study, the robust expansion could be significantly oversized. However, by using flexibility contracting as an alternative to conventional network expansion measures, some of the expansion costs can be reduced in the second stage of decision making, as the lower load growth scenario will have materialised. Specifically, in the two-stage two-scenario DNP problem flexibility contracted in the first stage for the duration of the first period would not need to be contracted again for the second stage. Furthermore, based on the assumption that only 50 % of the flexibility contracting costs need to be paid in case of non-activation, the NPV of the expansion costs is further reduced if scenario A materialises. Although the potential savings that would be achieved if scenario A were to materialise are relatively small in this particular case study, the value of flexibility in DNP under uncertainty has been demonstrated. This is due to the fact that flexibility can be contracted in much shorter timeframes than the usual lifetime of conventional network assets.

It is important to note that the relatively simple methodology introduced in Section 5.7.3 and applied in this Section has its limitations in showing the full value of flexibility. This is mainly due to the fact that the overall OF presented in Section 5.7.2 is not minimised, as the later stage decisions do not influence the first stage decision. From the point of view of stochastic optimisation, contracting flexibility is the only recourse decision available in the second decision stage that can reduce the OF value, as other investment decisions can only increase the OF value further. This is due to the fact that the lifetime of conventional network expansion assets is significantly longer than the duration of the flexibility contract, which is assumed to be less than or equal to the duration of each planning period. Let's assume that the decisions made in the second stage, in particular the recourse decisions that can reduce the OF value (flexibility contracting), would influence the decisions made in the first stage accordingly. Let's also assume that the load growth scenarios are weighted and that scenario B with the very high load growth is very unlikely. With sufficient flexibility available over the planning horizon, an optimal robust plan would likely include significantly higher amounts of contracted flexibility to replace conventional expansion. This is because the savings from not re-contracting flexibility in the second stage, if the likely scenario A materialises, are captured by the expected value in the OF. Such results can be obtained if the solution method successfully hedges recourse decisions in the second stage, or by applying two-stage stochastic optimisation using mathematical programming where flexibility contracting as a recourse decision is accurately modelled. While the latter method can guarantee optimality if a solution is found, the problem is difficult and no results have yet been obtained for realistic large-scale DNP. The first method of hedging may be promising to implement within a metaheuristic approach, with all the limitations of proving optimality. Another approach could be based on risk analysis, where the risk of ending up with an oversized network, as well as the opportunity of deciding not to re-contract flexibility in the latter decision stage, could be modelled as value at risk. If a good method is found to generate good candidate solutions, these could then be benchmarked against their risk value in a second decision step.

5.10 Conclusion

In this chapter single-stage and multistage multi-scenario DNP with conventional (i.e. transformers and lines) and non-conventional expansion measures (i.e. flexibility contracting) was treated. For this purpose, the models introduced in the previous chapters were used and the planning problem was extended to include the dimension of uncertainty. After a broader review of the concept of uncertainty and risk and its application to DNP, a higher level review of applicable and promising solution methods has been provided. Both the single-stage and multistage problems of DNP under uncertainty have been introduced and mathematically formulated, and a simple solution method for obtaining robust expansion plans/policies has been provided for both cases. Using those solution methods a case study was introduced. The case study has shown that a robust network expansion in face of significant load growth uncertainty leads to high network investment cost for grid assets with a very high lifespan (transformers and lines). Flexibility contracting as an alternative to conventional network expansion can reduce the risk of over-sizing the network for potential future load growth to some extend. These findings lead to the following considerations for future research. If the scenario tree would be modelled with weighted branches representing the probabilities of an individual scenario to materialise, the flexibility contract that might be renewed in the second decision stage, could be expressed as value at risk. In such a case, the multi-scenario multistage DNP method could be extended to contain a risk analysis approach in which the planners can lay out expansion policies and make investment decisions based on the experts expectations of the future and their level of risk-aversion. Such approach could be extended to additionally consider the value of lost load or more generally reliability in the OF of the multistage multi-scenario DNP problem. Doing so would enrich the risk-based planning methodology that would produce a expansion policy containing investment decisions, recourse decisions for future decision stages as well providing some insight on the overall risk involved at different stages of the scenario tree. In addition to such a risk analysis-based approach, stochastic optimisation with different solution methods seems promising to solve the problem at hand and to further explore the value of flexibility in long-term planning. One solution method could be based on mathematical programming, although the size and complexity of the DNP problem would probably need to remain relatively small. Another solution method could be based on extending the TS algorithm with methods for hedging flexibility contracts in order to properly consider the related recourse decisions in the second decision stage already in the first stage. Alternatively, the stages and scenarios could be embedded in the TS algorithm, such that each generated candidate solution is composed of a set of expansions over the number of stages, which cover the uncertainty modelled in the scenarios.

6 Conclusion, contributions and future work

This chapter, as the last chapter of the thesis, brings the work presented to a close. Firstly, the conclusions are discussed. Secondly, the contributions of this thesis are presented. Finally, promising future work in distribution network planning is proposed.

6.1 Conclusion

To conclude the thesis work undertaken, one can say that the effectiveness of Tabu Search (TS) for solving the distribution network planning problem with flexibility from demand response as an alternative to conventional network reinforcement was demonstrated. The respective single-stage distribution network planning model, based on the TS metaheuristic was introduced in Section 3. It has been proven successful to first generate a technically feasible but non-cost-optimal solution using a rather simple heuristic method, followed by the optimisation of that solution using TS. Particularly, the use of ejection chains has shown to be useful for exchanging non-conventional with conventional expansion measures. The use of TS as a metaheuristic optimisation algorithm provides considerable flexibility in incorporating domain-specific technical and regulatory features as well as planning requirements. This adaptability enables effective handling of large networks in an urban context, such as managing a network of 2762 buses. The case studies show that the use of flexibility contracting as an alternative to conventional reinforcement depends not only on the price of flexibility but also on the specific conditions in a feeder. Therefore, there are different discrete thresholds below which flexibility contracting is preferred to conventional reinforcement. In the case study on a large-scale realistic network presented in Section 3.6.2, it has been shown that using demand response, at flexibility cost of 5,000 €/MW and year, as an alternative to conventional expansion can reduce total costs by 7.5 % compared to the conventional expansion solution. Implementing this approach across an entire country or region's distribution network could result in significant savings, given the immense cost of expanding the distribution system to accommodate projected load growth and expansion of distributed energy resources.

- The implemented TS solution method is effective in solving the ADNP problem for realistic large-scale networks.
- Flexibility contracting as an alternative to conventional reinforcement depends on price of flexibility and on specific conditions in a feeder.

To solve the multistage distribution network planning problem, including flexibility contracting and conventional network reinforcement measures, the pseudo-dynamic forward fill-in method has been implemented in Section 4, using the previously developed single-stage model. The pseudo-dynamic multistage algorithm combined with TS does not guarantee optimality, but it is shown to work well and produce efficient results, while being easily scalable to solve distribution network planning problems in realistic large-scale distribution systems.

The value of flexibility in long-term distribution network planning is clearly demonstrated using the multistage planning approach. By using flexibility contracting, costly network investments with long asset lives can be deferred to the future, when the time value of money is lower and the required investments are more justified with respect to expected load growth. In the case study provided, flexibility contracting at a cost of 10,000 €/MW per year was shown to deliver total cost savings of 15.68 %. As the forward fill-in method is a pseudo-dynamic planning approach, it may not fully account for certain time-dynamic effects. Therefore, to address this limitation for the specific problem, it is advisable to explore alternative multistage pseudo-dynamic or preferably dynamic algorithms in future studies. In addition, it has shown that the integration of multistage distribution network planning with multi-scenario analysis is promising, particularly in terms of incorporating flexibility contracting to manage uncertainties in long-term distribution network planning.

- Flexibility contracting helps to defer costly network investments with long asset lifetime to the future, where the time value of money is lower and the investment is more justified related to expected load growth.

- Flexibility contracting can avoid investing in conventional network expansions with long asset lifetime at the same network asset location consecutively.

Finally, to cover long-term distribution network planning under uncertainty, both single-stage and multistage multi-scenario distribution network planning with conventional (i.e. transformers and lines) and non-conventional expansion measures (i.e. flexibility contracting) was introduced in Section 5. To include the dimension of uncertainty into the planning problem, it was possible to re-use the previously introduced models.

Following a comprehensive exploration of the concepts of uncertainty and risk and their relevance to distribution network planning, a thorough examination of potential higher-level solution methods was presented, showing their potential to meet planners' needs for planning under uncertainty. The mathematical formulations presented for both single-stage and multistage distribution network planning problems under uncertainty provide insight into the complexities to be considered in potential solution methods. The reuse of the previously developed models in the proposed solution methods has been shown to be effective in obtaining robust expansion plans or policies for single-stage and multi-stage planning under uncertainty. A case study was presented to illustrate the application of these solution methods. The case study showed that robust network expansion in the face of significant load growth uncertainty leads to high network investment costs for network assets with very long lifetimes (transformers and lines). The use of flexibility contracting as an alternative to conventional network expansion can, to some extent, reduce the risk of oversizing the network for potential future load growth.

- Flexibility contracting can reduce the risk of over-sizing the network for uncertain future load growth to some extend

6.2 Contributions

In the following, several contributions of this thesis to the state of the art in distribution network planning (DNP) and active distribution network planning are summarised.

- Development of a DNP model that provides efficient solutions for realistic large-scale networks.
- Extension of the model to an ADNP model providing a simple financial benchmark between flexibility contracting and conventional grid reinforcement.
- Analysis that uncovered the expansion decisions sensitivity to the price of flexibility.
- Extension of the model to multistage, to improve the ability to analyse the value of load flexibility, in particular by supporting the deferral of network investments.
- Mathematical formulations of the single-stage and multistage ADNP problems under uncertainty.
- Proposal of a generalisable single-stage and two-stage robust ADNP methodology under uncertainty that can capture some value of flexibility.

The first contribution is the development of a DNP model that provides good solutions for large realistic networks, e.g. at city scale. The single-stage peak-load DNP model can use a wide range of scenario inputs, considering different growth of load and distributed generation, expansion technologies and their prices, as well as regulatory parameters (i.e. WACC, regulated depreciation period of assets). The developed model is based on the TS metaheuristic, as approaches based on mathematical programming reach their limits due to the size and complexity of the computational problem at hand. The software tool is implemented in Python 3, using several powerful open source software packages such as numpy (Harris et al., 2020), pandas (McKinney, 2010), pypower based pandapower (Thurner et al., 2018), igraph (Csardi et al., 2006). The software has been developed with a focus on scalability, modularity, the ability to easily extend functionality and debuggability, taking into account the multifaceted nature of the DNP problem in real-world applications.

A second contribution to the state of the art is the extension of the above decision support tool for the use of load flexibility from demand response as an alternative to conventional network reinforcement for future peak load in a realistic large-scale distribution network. Notably, the functionality added to the DNP tool is generalisable to other alternative solutions by providing a simple financial benchmark between the latter and conventional grid reinforcement. In this work, the resulting model is used to study the conventional and non-conventional network expansions required to accommodate the future peak load caused mainly by load growth in the form of electric vehicle chargers in a Spanish city of approximately 160,000 inhabitants. It is assumed that flexibility contracts can be activated at a given set of nodes in the network, while it is up to the optimisation algorithm to decide which of these flexibility contracts will ultimately be activated.

After completing the work on the single-stage DNP model, a pseudo-dynamic multistage DNP approach is proposed. The third contribution is that the developed model allows to demonstrate the value of contracting load flexibility in multistage DNP, allowing to postpone some network investments as well as to avoid some investments in the overall planning period. The proposed multistage DNP approach improves the ability to analyse the value of load flexibility, in particular by supporting the deferral of network investments, which is usually not observed in single-stage DNP approaches. To the authors' knowledge, this is the first time that TS has been applied in pseudo-dynamic DNP using load flexibility as an non-conventional expansion measure.

A fourth contribution to the state of the art is the proposal of a methodology for single-stage and two-stage DNP under uncertainty that is generalisable to multistage cases. The multistage, multi-scenario DNP model uses flexibility contracting as an alternative to conventional network expansion measures and provides robust expansion policies for multistage problems under deep uncertainty. Although the solution method presented does not fully capture the value of flexibility in distribution expansion planning, some of the value has been demonstrated. That is, taking into account robust planning, it has been shown that flexibility contracting as an alternative to conventional network expansion can reduce overall expansion costs in the event that the extreme scenario does not materialise. However, this is likely to reflect only a fraction of the true value of flexibility, while the rest of the value is not captured by the proposed methodology. This other part of the value of flexibility would be captured by a model that takes into account the later stage expansion decisions and the probability of the need for them in the first stage decision.

6.2.1 List of publications

Articles published in peer-reviewed academic journals

- Ziegler, D. U., G. Prettico, C. Mateo, and T. Gómez San Román (2023). "Methodology for integrating flexibility into realistic large-scale distribution network planning using Tabu search". International Journal of Electrical Power & Energy Systems 152, p. 109201. issn: 0142-0615. doi: 10.1016/j.ijepes.2023.109201.

- Valarezo, O., T. Gómez, J. P. Chaves-Avila, L. Lind, M. Correa, D. Ulrich Ziegler, and R. Escobar (2021). "Analysis of New Flexibility Market Models in Europe". Energies 14:12, p. 3521. issn: 1996-1073. doi: 10.3390/en14123521.

Articles currently under peer-review in academic journals

- Ziegler, D. U., C. Mateo, T. Gomez San Roman, and G. Prettico (2023). Multistage distribution expansion planning leveraging load flexibility. (2nd revision) url: `https://www.iit.comillas.edu/publicacion/workingpaper/es/498/Multistage_distribution_expansion_planning_leveraging_load_flexibility` (visited on 09.04.2023).

Articles presented at international conferences

- Ziegler, D. U., 2021. Achieving Active Distribution Networks through Operational and Architectural Aspects Analysis: A Methodology for Long-Term Planning. Presented at CIRED 2021 Online, 20-23.09.2021.

Reports of European research projects

- Troncia, M., D. U. Ziegler, T. Gómez, J. P. Chaves, E. Beckstedde, L. Meeus, J. Villar, A. Oliveira, et al. (2021). Deliverable: D1.3 - Challenges and opportunities for electricity grids and markets. Technical report H2020–LC-ES-1-2019. doi: 10.3030/864334.
- Gouveia, C., E. Alves, J. Villar, R. Ferreira, R. Silva, J. P. Chaves, T. Gómez, L. Herding, N. Morell, M. Rivier, D. U. Ziegler, et al. (2021). Deliverable: D1.2 - Observatory of research and demonstration initiatives on future electricity grids and markets. Technical report H2020 – LC-ES-1-2019. doi: 10.3030/864334.
- Beckstedde, E., M. Leonardo, T. Gómez, L. Herding, M. Correa, N. Morell, O. Valarezo, J. P. Chaves, D. U. Ziegler, et al. (2020). Deliverable: D1.1 - Characterisation of current network regulation and market rules that will shape future markets. Technical report H2020–LC-ES-1-2019. doi: 10.3030/864334.

6.3 Future work

The potential future work identified throughout the thesis is summarised in the following.

- Analysis of the impact of a range of relevant energy system scenarios.
- Modelling the use of other flexibilities such as from smart grid solutions.
- TS performance improvements through testing of various diversification and intensification strategies.
- Hybridisation of the TS algorithm to combine its strength with those of population-based metaheuristics or mathematical programming.
- Regarding multistage ADNP under uncertainty, different optimisation strategies could be tested that identify relevant sets of efficient solutions (e.g. generate more candidate solutions), incl. testing of techniques to benchmark such solutions.
- Extending the problem to cover reliability (e.g. VoLL).
- Probability of load growth scenarios could be considered, allowing a value-at-risk modelling of expansion decisions.
- Extending the TS approach with hedging mechanism for flexibility contracts (in the recourse decision)

Regarding the developed DNP model, some recommendations for further research include analysing the impact of a range of relevant energy system scenarios, modelling smart grid technologies and improving the performance of the TS algorithm. Modelling the use of flexibility provided by smart grid technologies, distribution transformers with on-load tap changers seem particularly timely and relevant to implement and investigate. Also, planning with more complex decentralised grid automation systems would provide for an interesting and relevant case study. Regarding the performance of the TS algorithm, further studying alternative intensification and diversification strategies could provide relevant performance gains. Furthermore, the hybridisation of the TS algorithm, such as by combining its strength with those of population-based metaheuristics or mathematical programming, promises even further performance gains.

As the forward fill-in method for multistage DNP described in Section 4.4 is a pseudo-dynamic planning method, some time-dynamic effects may not be captured. It is therefore recommended that future research investigate alternative multistage pseudo-dynamic or ideally dynamic algorithms for the problem at hand. Also, combining multistage DNP with multi-scenario analysis would be of great value, especially with respect to the value of flexibility contracting to deal with uncertainty in long-term DNP planning.

Regarding multistage DNP under uncertainty, some future work should be done to test different optimisation strategies to identify a relevant set of efficient solutions from which the selection of the preferred expansion policy can be made. This can include algorithms to generate more diverse sets of candidate solutions. Also various selection techniques could be tested, benchmarking the effect of different decision criteria on the expansion cost and risk involved. Involving risk of oversizing the network is particularly relevant if uncertainty is modelled probabilistically and the risk-aversion of the planner is to be considered in investment decision making. To improve the existing approach, it can be extended to include the value of lost load or, more broadly, reliability in the objective function of the multistage, multi-scenario network planning problem. This enhancement would enrich the risk-based planning method by providing valuable information on the overall risk associated with different stages of the scenario tree, including investment decisions and recourse decisions for future decision stages. By considering the value of lost load and reliability, the planning methodology becomes more comprehensive and facilitates a holistic assessment of risk and decision making in distribution network planning. As an alternative approach to this method of generating solutions, and selecting the preferred solution from those, stochastic optimisation is particularly promising. Stochastic optimisation, using a variety of solution methods, holds promise for addressing the current problem and for exploring the potential benefits of flexibility in long-term distribution network planning. One viable solution approach involves the use of mathematical programming, although the size and complexity of the distribution network planning problem may limit its application to relatively smaller problem instances. Another solution approach is to extend the Tabu Search algorithm to include techniques for the incorporation of flexibility contracting, thereby allowing the consideration of appropriate recourse decisions in the second decision stage during the first decision stage itself. Furthermore, leveraging the developed models capabilities, interesting case studies for DNP in the context of the ongoing energy transition and the changing global security context could provide valuable insights and potential strategic impact for stakeholders in the distribution network planning, such as policy makers, distribution system operators and financial institutions. In this sense, the developed models can also support the creation of a pragmatic digital twin of the European electricity system that can provide insights beyond investment planning. Such insights would be particularly valuable in the context of (cyber) risk preparedness and climate change mitigation.

A Tabu Search: Supplementary information

A.1 General definitions of terms used in the Tabu Search implementation

The TS implementation of this thesis is based on the following basic TS definitions.

Search strategy: Different search strategies can be used within the TS procedure. Among the most prominent are steepest search and best-improving search. Steepest search is a search strategy in which the neighbour with the best move value is selected in each iteration. Only moves with positive move values are allowed. The search procedure stops when there are no moves with a positive value in a given neighbourhood. Best-improving search works on the same principles, the main difference being that moves with zero or negative move values are also allowed.

Search space: All possible solutions or network candidates (potential solutions) that can be visited during the search process. The network candidates may include infeasible solutions if necessary for the search process.

Network candidate: A candidate network, also called a neighbour, is a variation of the initial network or the current best network, described by the initial network and the sum of all network expansions applied.

Candidate list strategy: A candidate list strategy reduces the computational cost of examining the neighbourhood of the current best candidate by narrowing down to an appropriate set of candidates to be examined.

Current best candidate: The current-best candidate is the network candidate that was accepted as the best candidate in the previous iteration.

Move: An operation involving one or more local modifications of network elements that creates a new candidate network solution.

Neighbourhood: The neighbourhood consists of all or a selection of network candidates that can be created by applying the available moves to the current best solution.

Neighbourhood structure: The neighbourhood structure describes how the neighbourhood of the current best solution is created.

Neighbourhood size: The size of the neighbourhood is defined by the number of neighbourhood solutions created from the current best solution in one iteration.

Insertion of moves: Insertions of moves describe changes to specific network elements of a candidate solution that create a new candidate or a neighbour of the current best solution. While moves describe what kind of network element or combination of elements is changed, insertions describe where and when these changes are made. Moves can be inserted either randomly or at the most strategic positions (i.e. at relevant nodes or branches) within the network.

Insertion complexity: Insertions of moves can have different levels of complexity. Insertions can be relatively simple applications of moves on specific network elements, such as the addition or removal of a parallel transformer or a combination of such changes. More complex insertions can be described as sequences of coordinated moves, so called ejection chains (Gendreau et al., 2019). Lastly, cross-exchange insertions describe the swapping of whole ejection chains to create new candidate solutions (Gendreau et al., 2019).

Move value: The move value is the difference between the two objective function values of the solution before and after inserting a move. Therefore moves with a positive move value are improving moves, while those with a move value less than or equal to zero are non-improving moves.

Recency-based attributive memory: Attributes that occur in recently visited solutions are stored to prevent them from becoming part of the neighbourhood and thus preventing revisiting.

Tabu tenure: The tabu tenure describes the number of iterations until an attribute loses its tabu active state. The tabu tenure can be static or dynamic. In the latter case, tabu tenure can vary systematically or probabilistically.

A.2 TS moves implemented

The following TS moves for transformer expansion have been implemented in the model of this thesis.

The following TS moves for line expansion have been implemented in the model of this thesis.

The following TS moves for non-conventional grid expansion based on flexibility contracting has been implemented in the model of this thesis.

move	description	standard type	rating [kVA]	move alterations
0	no change	n.a.	n.a.	n.a.
1	replacement	0.4 MVA 20/0.4 kV	400	0
2	replacement	0.63 MVA 20/0.4 kV	630	0;1
3	replacement	1 MVA 20/0.4 kV	1000	1;2
4	parallel addition	0.4 MVA 20/0.4 kV	400	2;3
5	parallel addition	0.63 MVA 20/0.4 kV	630	3;4
6	parallel addition	1 MVA 20/0.4 kV	1000	4;5
7	two parallel add.	combine: 4 & 5	1030	5;6
8	Repl. and parallel add.	combine: 2 & 5	1260	3;5;6
9	two parallel add.	combine: 5 & 5	1260	6;7
10	Repl. and parallel add.	combine: 2 & 6	1630	5;8
11	two parallel add.	combine 5 & 6	1630	7;9
12	Repl. and parallel add.	combine 3 & 6	2000	8;10
13	two parallel add.	combine 6 & 6	2000	9;11

Table A.1: Transformer moves implemented in the version of this thesis

move	description	move alterations
0	no change	1
1	one line parallel addition	0;2
2	two lines parallel addition	0;1

Table A.2: Line moves implemented in the version of this thesis

move	description	move alterations
0	no flexibility contracting	1
1	contract flexibility type A	0

Table A.3: Flexibility moves implemented in the version of this thesis

B Stochastic optimisation formulation for multistage multi-scenario distribution network planning

In the following the problem formulation for the generalisation of the two-stage DNP under uncertainty problem to the multistage DNP under uncertainty is presented, based on a literature review on stochastic programming (Birge et al., 2011; Shapiro et al., 2007).

B.1 Two-stage stochastic programming generalisation

In this section, the two-stage multi-scenario DNP problem formulation presented in Section 5.7.2 is generalised. Here it is assumed that uncertainty is expressed in a finite number of scenarios $s \in \Omega_S$ The two-stage problem with recourse decisions, as presented in Section 5.7.2, can be generalised to equation B.1.

$$\min \quad c^\intercal x + \mathbb{E}[\mathbb{Q}(x, s)] \tag{B.1}$$

In this generalised form, the first stage OF term of equation B.1, representing the *here and now* decision is defined to be the first stage term of the formulation in equation (5.20) presented in Section 5.7.2, as shown in equation (B.2). Here, c is a vector representing the expansion cost expressed in the first term of the OF shown in equation (5.20), or the right hand side of equation (B.2), and equations (5.27-5.31), respectively. The first stage decision vector $x \in \{0, 1\}$ contains all the binary decision variables for gird expansion based on the installation of transformers and lines, as well as the contracting of flexibility that are expressed as $(b_{br_{ij,tra}}, b_{br_{ij,li}}, b_{i,fl})$, in equation (5.20). Equation (B.1) is subject to the same operational and investment constraints as equation (5.20) described in Section 5.7.2.

$$c^\intercal x := \sum_{i=1}^{n_{p1}} \frac{1}{(1+r)^i} (A(G_{p1}) + A(F_{p1})) \tag{B.2}$$

The second stage OF term represents the expected value function shown in equation (B.1). Where $\mathbb{Q}(x, s)$ is the expected value function, that expresses the expected value of the recourse function containing the *wait and see* decisions, that depend on the first stage decisions in x and the realisation of the uncertain parameters expressed in scenario s. Here, the expected value of

$\mathbb{Q}(x, s)$ is the optimal value of the second-stage problem, shown in equation (B.3), based on the scenarios $s \in \Omega_S$.

$$\mathbb{Q}(x, s) := \min \quad q(x, s)^\intercal y \tag{B.3}$$

Here, $q(x, s)^T y$ is defined as the second OF term in equation (5.20), as shown in equation (B.4), where equations (5.27-5.31) hold as shown in Section 5.7.2. Here, q is a vector representing the second stage expansion cost, which depend on the binary first stage decisions $x \in \{0, 1\}$, the binary second stage decisions $y \in \{0, 1\}$ as well as the scenario $s \in \Omega_S$.

$$q(x, s)^\intercal y := \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}(A(G_{p1}) + A(G^s_{p2}) + A(F^s_{p2})) \tag{B.4}$$

And therefore, the expected recourse function as in equation (B.5), that finds the average value of the second-stage expansion based on the uncertainty modelled in n_s scenarios $s \in \Omega_S$.

$$\mathbb{E}\left[\sum_{s=0}^{n_s}\left(\sigma^s * \sum_{i=n_{p1}+1}^{n_{p2}} \frac{1}{(1+r)^i}(A(G_{p1}) + A(G^s_{p2}) + A(F^s_{p2}))\right)\right] \tag{B.5}$$

Overall, this results in the general two-stage DNP problem formulation with recourse decisions in the second stage, shown in equation (B.1).

B.2 Generalisation to multistage stochastic programming

In the previous section, the generalisation of the two-stage stochastic programming problem for the two-stage DNP under uncertainty problem presented in Section 5.7.2, was defined. In the following, the two-stage problem is generalised to a multistage formulation. This problem type is generally referred to as multistage stochastic integer programming (MSIP). As previously, uncertain parameters are modelled in a finite set Ω_S containing n_s discrete scenarios s over P stages. The resulting generalised scenario tree is shown in Figure B.1, where from each node in each stage, the corresponding scenarios emerge, here illustrated by the outer three dots above and below the path in the middle.

The mathematical formulation of the two-stage problem presented in the previous Section B.1, generalised to a multistage stochastic optimisation problem formulation is shown in equation (B.6).

$$\min \quad c^\intercal x_1 + \mathbb{E}[\mathbb{Q}_2(x_2, s_2) + \mathbb{E}[\cdots + \mathbb{E}[\mathbb{Q}_T(x_T, s_T)]]\cdots] \tag{B.6}$$

In this generalised form, the first stage OF term of equation B.1, representing the *here and now* decision is defined to be the first stage term of the formulation in equation (5.20) presented in Section 5.7.2, as shown in equation (B.2). Here, c is a vector representing the expansion cost expressed in the first term of the OF shown in equation (5.20), or the right hand side of equation (B.2), and equations (5.27-5.31), respectively. The first stage decision vector $x \in \{0, 1\}$ contains all the binary decision variables for gird expansion based on the installation of transformers and lines, as well as the contracting of flexibility that are expressed as $(b_{br_{ij,tra}}, b_{br_{ij,li}}, b_{i,fl})$, in equation

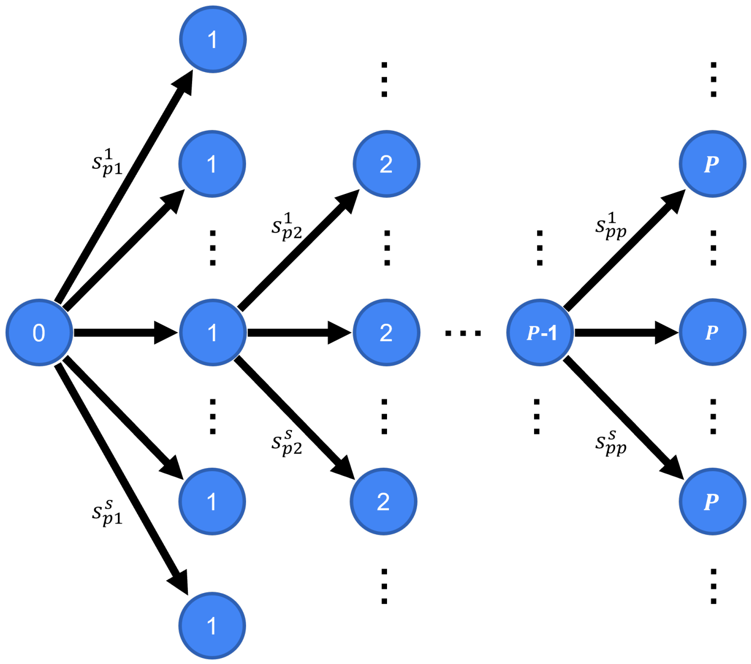


Figure B.1: Generalised scenario tree for multistage multi-scenario uncertainty modelling

(5.20). Equation (B.1) is subject to the same operational and investment constraints as equation (5.20) described in Section 5.7.2.

The OF shown in equation B.6, is subject to the constraints expressed in equation (B.7), where Wy balances any inconsistencies in $Tx \leq b$ based on the first stage decisions x.

$$h_p^s \geq W^s y^s - T^s x \quad \forall s \in \Omega_S, \forall p \in P \tag{B.7}$$

Equation (B.7) is a generic function representing all investment and operational constraints in all scenarios over all planning periods.

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