The increasing share of renewable energy sources in the power system necessitates new planning methods for power systems. On the one hand, flexible operational measures must be included in planning. On the other hand, conventional measures have to be considered. In this thesis, a multi-year planning strategy for meshed high voltage (HV) systems is proposed considering operational flexibility as well as conventional planning measures. The defined optimization problem is solved by a hybrid optimization algorithm combining the advantages of heuristic and mathematical programming approaches. A reduction of the high computational effort of time series simulations is achieved by several strategies, which are integrated into the open-source tool pandapower. Furthermore, several machine learning algorithms are compared. The developed hybrid optimization method is a combination of the Iterated Local Search metaheuristic and a linear optimization model. This combination increases convergence while reducing simulation time in comparison to the existing methods. Finally, two case studies show the applicability of the developed planning framework for a real HV power system model.
Abstract

The increasing share of renewable energy sources (RES) in the power system necessitates new planning methods for power systems systems. On the one hand, flexible operational measures must be included in planning. On the other hand, conventional measures have to be considered. An integrated optimization of both measures is needed. This integrated optimization requires time series simulations of the power system in comparison to traditional worst case planning approaches. The high voltage (HV) level has the highest security requirements of all distribution levels. Typically, HV systems have a meshed topology, and the single contingency policy (SCP) is additionally considered in planning. Finding a trade-off between computational effort and solution quality is the main challenge when considering time series simulations and the SCP. A power system planning strategy is needed, which is able to find an investment decision for multiple years within a realistic simulation time.

In this thesis, a multi-year planning strategy for meshed HV systems is proposed considering operational flexibility as well as conventional planning measures. The defined optimization problem is solved by a hybrid optimization algorithm combining the advantages of heuristic and mathematical programming approaches. A reduction of the high computational effort of time series simulations is achieved by several strategies, including a custom Newton-Raphson power flow implementation and an efficient time series module, which are integrated into the open-source tool pandapower. Furthermore, several machine learning algorithms are implemented and compared to approximate bus voltages and power line loadings. Operational simulation models of two curtailment strategies and two storage system operational models are implemented. An exhaustive evaluation of four optimization metaheuristics, three mathematical programming approaches, and the developed hybrid approach is shown.

Results are validated on four realistic benchmark systems and a real power system model. Several benchmarks show that the implemented methods significantly reduce the calculation time of time series simulations. The Newton-Raphson implementation is up to 30 times faster than comparable open-source versions. A further reduction of the simulation time is possible with the implemented regres-
sion method based on an artificial neural network (ANN). The ANN correctly identifies more than 99.4% of all critical time steps for the benchmark cases, including contingency situations when trained with 10% of the time series data of one year.

The developed hybrid optimization method is a combination of the Iterated Local Search metaheuristic and a linear optimization model. This combination increases convergence while reducing simulation time in comparison to the existing methods. The hybrid strategy is the only method of all compared algorithms, which finds valid solutions in large optimization space, including replacement and switching measures. Additionally, the simulation time is reduced by up to 80% for the benchmark cases. Finally, two case studies show the applicability of the developed planning framework for a real HV power system model. In these case studies, curtailment of energy from RES and line replacement measures are regarded for a planning horizon of 12 years. The results show that a reduction of up to 60% of the total expenditures, compared to the worst case method, is possible by combining the optimization of RES curtailment and line replacement measures. Expenditures can further be reduced by 4% when using operational flexibility from storage systems.
Kurzfassung


als 99.4\% aller kritischen Zeitschritte für die Benchmarksysteme, einschließlich \(N\)-1-Situationen, wenn mit 10\% der Zeitreihendaten eines Jahres trainiert wird.

Acknowledgements

This thesis is partly supported by the German Federal Ministry of Economic Affairs and Energy (BMWI) and the Projektträger Jülich GmbH within the framework of the projects *OpSimEval* (funding number 0325782B) and *SpinAI - Spitzenkappung und Netzausbauplanung - Automatisiert und Intelligent* (funding number 0350030B). The author is solely responsible for the content of this publication.
Danksagung

Diese Dissertation ist während meiner Tätigkeit am Fachgebiet Energiemanagement und Betrieb elektrischer Netze – $e^2_n$ entstanden. Rückblickend auf die letzten vier Jahre möchte ich mich bei allen Kollegen, Freunden und meiner Familie für die großartige, lehrreiche und intensive Zeit bedanken.

Zunächst danke ich meinem Doktorvater Prof. Dr.-Ing. Martin Braun, der mich bei meiner fachlichen und persönlichen Weiterentwicklung stets unterstützt hat. Vom ersten Tag an schenkte er mir vollstes Vertrauen in meine Arbeit und unterstützte mein Engagement im VDE und der CIGRE sowie mein promotionsbegleitendes MBA-Programm. Eine solche Unterstützung ist keine Selbstverständlichkeit, für die ich äußerst dankbar bin! Bei meinem Zweitgutachter Prof. Lutz Hofmann danke ich mich für die Begutachtung dieser Doktorarbeit und den fachlichen Rat.


und Robert, die für alle Anliegen stets ein offenes Ohr hatten. Auch den Kolleginnen und Kollegen am Fraunhofer IEE danke ich für die schöne Zeit. Dazu gehören Alex, Jan, Simon, Roman, Daniel, Daniel, Mike, Frank, Johannes, Chenjie, Fabian, Markus, Haonan, Tanja, Erika, Benjamin und Andrea.


List of the Author’s Publications

Journal Publications

First Authorship


• Florian Schäfer, Jan-Hendrik Menke, Martin Braun: *Prediction of Power Flow Results in Time-Series-Based Planning with Artificial Neural Networks and Data Pre-Processing*, CIRED - Open Access Proceedings Journal, 2020 - to be published


Co-Authorship

Book Chapter

Co-Authorship


Conference Proceedings

First Authorship


• Florian Schäfer, Jan-Hendrik Menke, Martin Braun: *Contingency Analysis of Power Systems with Artificial Neural Networks*, IEEE International Conference on Communications, Control, and Computing Technologies for Smart
Grids (SmartGridComm), 2018, https://doi.org/10.1109/SmartGridComm.2018.8587482


- Florian Schäfer, Jan-Hendrik Menke, Martin Braun, Machine Learning in Power Systems, VDE TecSummit, Berlin 2018

**Co-Authorship**


List of Supervised Theses

- Christian Jähner: *Auswahl von Netznutzungsfällen aus Zeitreihen zur Netzausbauplanung im Hochspannungs-Verteilnetz*, Master Thesis at the University of Kassel, 2020

- Martin Scharf: *Untersuchung der Auswirkung von Speicherbetriebsführungen auf die Netzauslastung von Verteilungsnetzen unter Anwendung von zeitreihenbasierten Lastflusssimulationen*, Master Thesis at the University of Kassel, 2018
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Acronyms

AC
Alternating current
ADAM
Adaptive moment estimation
ADASYN
Adaptive synthetic sampling
ANN
Artificial neural network
BBM
Bus-branch model
CAPEX
Capital expenditures
CHP
Combined heat and power
CPU
Central Processing Unit
CRS
Compressed row storage
CV
Cross validation
DC
Direct current
DCF
Discounted cash flow
DER
Distributed energy resource
DG
Distributed generator
DSM
Demand side management
DSO
Distribution system operator
DT
Decision Tree
ED
Economic dispatch
EEG
Erneuerbare Energien Gesetz
EHV
Extra high voltage
EnWG
Energiewirtschaftsgesetz
ET
Extremely Randomized Tree
FN
False negative
FNR
False negative rate
FP
False positive
FPR
False positive rate
FWA
Fireworks Algorithm
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
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<tbody>
<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
</tr>
<tr>
<td>GPU</td>
<td>Graphics Processing Unit</td>
</tr>
<tr>
<td>GWO</td>
<td>Grey Wolf Optimizer</td>
</tr>
<tr>
<td>HC</td>
<td>Hill Climbing</td>
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<tr>
<td>HV</td>
<td>High voltage</td>
</tr>
<tr>
<td>IAL</td>
<td>Installation of additional lines</td>
</tr>
<tr>
<td>ICT</td>
<td>Information and communication technology</td>
</tr>
<tr>
<td>ILS</td>
<td>Iterated Local Search</td>
</tr>
<tr>
<td>k-NN</td>
<td>k-Nearest Neighbors</td>
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<td>LV</td>
<td>Low voltage</td>
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<tr>
<td>MIP</td>
<td>Mixed integer programming</td>
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<tr>
<td>ML</td>
<td>Machine learning</td>
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<tr>
<td>MLP</td>
<td>Multilayer perceptron</td>
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<tr>
<td>MINLP</td>
<td>Mixed integer non-linear programming</td>
</tr>
<tr>
<td>MV</td>
<td>Medium voltage</td>
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<tr>
<td>NNZ</td>
<td>Number of non zero</td>
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<td>NPV</td>
<td>Net present value</td>
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<td>NR</td>
<td>Newton Raphson</td>
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<td>OPEX</td>
<td>Operational expenditures</td>
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<td>OPF</td>
<td>Optimal power flow</td>
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<tr>
<td>PCA</td>
<td>Principal Component Analysis</td>
</tr>
<tr>
<td>PF</td>
<td>Power flow</td>
</tr>
<tr>
<td>PSO</td>
<td>Particle Swarm Optimization</td>
</tr>
<tr>
<td>PV</td>
<td>Photovoltaic</td>
</tr>
<tr>
<td>QC</td>
<td>Quadratic convex</td>
</tr>
<tr>
<td>ReLu</td>
<td>Rectified linear unit</td>
</tr>
<tr>
<td>REPL</td>
<td>Replacements</td>
</tr>
<tr>
<td>RES</td>
<td>Renewable energy sources</td>
</tr>
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<td>RF</td>
<td>Random Forest</td>
</tr>
<tr>
<td>RTS</td>
<td>Reliability Test System</td>
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<tr>
<td>SB</td>
<td>SimBench</td>
</tr>
<tr>
<td>SCP</td>
<td>Single contingency policy</td>
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<td>SD</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>SDP</td>
<td>Semidefinite programming</td>
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<tr>
<td>SMOTE</td>
<td>Synthetic minority oversampling technique</td>
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<tr>
<td>Acronym</td>
<td>Definition</td>
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<tr>
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<tr>
<td>SOC</td>
<td>Second order conic</td>
</tr>
<tr>
<td>SSO</td>
<td>Switching state optimization</td>
</tr>
<tr>
<td>TN</td>
<td>True negative</td>
</tr>
<tr>
<td>TOTEX</td>
<td>Total expenditures</td>
</tr>
<tr>
<td>TP</td>
<td>True positive</td>
</tr>
<tr>
<td>TSO</td>
<td>Transmission system operator</td>
</tr>
<tr>
<td>VPP</td>
<td>Virtual power plant</td>
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<tr>
<td>WPP</td>
<td>Wind power plant</td>
</tr>
<tr>
<td>XGB</td>
<td>XGBoost</td>
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</tbody>
</table>
Acronyms
Symbols

\( A \)       annuity
\( B \)       set of branches
\( B_{ij} \)   line susceptances
\( C_{all} \)  fixed percentage of OPEX
\( C_s \)      consumption related cost
\( E \)       energy
\( E_g \)     generated energy
\( E_c \)     curtailed energy
\( G \)       set of generators
\( G_{ij} \)  line conductance
\( G_{RES} \) renewable energy source generators
\( \Im \)     imaginary part of complex numbers
\( I \)       current
\( I_{\%} \)   relative branch current
\( I_r \)     rated current
\( I_{ij} \)  complex branch current
\( J \)       Jacobian matrix
\( K_0 \)     acquisition cost
\( M \)       binary measure set
\( |M| \)     cardinality of a measure set
\( N \)       set of buses
\( N_{al} \)  number of additional lines
\( N_B \)     number of branches
\( N_d \)     number of disconnected buses
\( N_{lc} \)  number of load cases
\( N_{pq} \)  number of \( PQ \)-buses
\( N_{pv} \)  number of \( PV \)-buses
Symbols

\( N_{pvpq} \) number of PV- and PQ-buses
\( N_s \) number of storage systems
\( N_{sw} \) number of switches
\( P \) real power
\( P_D \) real power demand
\( P_g \) real power generation
\( P_{\text{max}}^{g,k} \) upper real power generation limit
\( P_{\text{min}}^{g,k} \) lower real power generation limit
\( P_N \) rated power
\( Q \) reactive power
\( \Re \) real part of complex numbers
\( R \) set of reference buses
\( S \) complex power
\( S_{bus} \) bus power injection matrix
\( S_D \) complex power demand
\( S_{ij} \) branch complex power flow
\( S_g \) complex power generation
\( S_{\text{max}}^{g,k} \) complex upper generation limit
\( S_{\text{min}}^{g,k} \) complex lower generation limit
\( \theta_{ij} \) angle of branch admittance between bus \( i \) and \( j \)
\( \theta_{ij}^{\Delta_l} \) branch voltage angle lower boundary
\( \theta_{ij}^{\Delta_u} \) branch voltage angle upper boundary
\( V \) complex bus voltage
\( V_n \) nominal voltage magnitude
\( V_r \) reference bus voltage
\( V_m \) voltage magnitude
\( V_k \) short circuit voltage
\( \vartheta_{\text{max}} \) max. operating temperature of a power line
\( X_{ij} \) branch reactance
\( Y_{\text{bus}} \) complex nodal admittance matrix
\( Y_{ij} \) complex admittance between bus \( i \) and \( j \)
\( \alpha_l \) binary decision variable for branch replacements
\( \beta_{al} \) binary decision variable for additional power lines
\( \gamma_{sw} \) binary decision variable for switches
Symbol | Description
--- | ---
$\delta$ | bus voltage angle
$\eta^c$ | charging efficiency
$\eta^d$ | discharging efficiency
$\lambda$ | interpolation hyperparameter
$a_n$ | annuity factor
$c_{al}$ | cost of additional lines
$c_l$ | cost of branch replacements
$c_{sw}$ | cost of switching measures
$e_i$ | additive error
$e^l$ | lower energy rating
$e^u$ | upper energy rating
$e_{t=0}$ | state of charge at $t = 0$
i$_r$ | interest rate
$i_{ij}^u$ | branch current limit
$j$ | imaginary unit
$p_a$ | probability
$p^c$ | charge rating
$p^d$ | discharge rating
$p_i^l$ | lower injection limit at time $t$
p$_{self}$ | relative self discharge rating
$p_{ij}^u$ | upper branch flow limit
$p_t^u$ | upper injection limit at time $t$
$q$ | interest factor $q = i + 1$
s | optimization solution candidate
$s^*$ | current best optimization solution
$s_{ij}^u$ | branch apparent power limit
t | time
$v_{i}^{\text{max}}$ | upper voltage boundary
$v_{i}^{\text{min}}$ | lower voltage boundary
$v_k$ | relative short circuit voltage
$y_i$ | true value of a dataset
$\hat{y}_i$ | predicted output value
1 Introduction

1.1 Motivation

Historically, power systems were designed to supply customers with electricity, generated by large power plants, according to the real-time demand. Times of peak consumption, therefore, determined the maximum loading of power transformers, power lines, and other equipment [1]. With the rising share of distributed renewable energy sources (RES) of the total installed capacity, a shift in the power system takes place. Germany, together with China and the US, is one of the leading economies to integrate RES worldwide [2]. In Germany, the share of RES was 52% of the installed power and 36% of the total consumed electric energy in 2017 [3]. The federal network agency of Germany expects a further growth of up to 75% of installed capacity in 2035 [4]. Figure 1.1 (a) shows the development of the capacity of RES in comparison the share of fossil fuels. In 2009, the installed power of fossil was 104 GW, which is expected to decline by 28% to a minimum of 69 GW in 2030 (Scenario C of [4]). Simultaneously, the share of RES is expected to further increase up to 76%, and a capacity of 220 GW in the same year. The federal network agency expects the largest installed capacity from wind- and solar-powered plants [4].

These power plants are, with a majority of 97%, installed at the distribution and sub-transmission levels in Germany [5]. High equipment loadings are the result in the power system, which are caused by a simultaneous high feed-in from distributed generators. Therefore, power system planning strategies have to consider situations of high in-feed of RES with low consumption at the same time [6]. RES do not generate electricity on demand, in comparison to fossil fueled power plants,
Figure 1.1: (a) Increase of RES in Germany and prognoses for 2025-2035. The percentage value is the share of RES of the total installed capacity. (b) Operational flexibility today and expected increase by type in comparison to 2017 [3–5]. A, B, and C are scenarios from [4].

but in times of high wind speed and solar radiation. Storage systems and additional flexibility from the demand-side can solve this issue by balancing load and demand [7]. The federal grid agency expects an increase of such operational flexibility from 1.9 GW in 2017 up to 23.7 GW in 2035 [4]. This increase equals a factor of 12 times the current amount as depicted in Fig. 1.1 (b).

In Germany, several laws regulate the integration of RES, including the energy industry act (ger. Energiewirtschaftsgesetz (EnWG)) and the renewables energy act (ger. Erneuerbare Energien Gesetz (EEG)). In their former versions, these laws stated that the grid infrastructure must be able to integrate 100% of the energy generated by RES and that system operators have to provide the appropriate infrastructure to transport all energy generated by RES [8, 9]. This requirement leads to rising investments in the infrastructure and high operational expenditures (OPEX) for transmission system operators (TSOs) and distribution system operators (DSOs). In Germany, the total expenditures increased from € 6.6 billion in 2009 to € 11.3 billion in 2019. For TSOs, the majority (88.9\%) of the total expenditures are capital expenditures (CAPEX). DSOs, on the other hand, have more balanced expenditures resulting from OPEX and CAPEX. Figure 1.2 shows this increase in expenditures and highlights that the majority accrues at the distribution and sub-transmission level, which is part of the distribution level in Germany [10].
Increasing Operational Expenditures

A technical consequence of the increasing amount of RES is a rising number of contingencies at all voltage levels. The grid infrastructure is reaching its limits because of high power flows (PFs); reverse PFs from lower voltage levels and possible voltage deviations from the nominal voltage [10, 11]. These problems are mitigated by using reserve generation capacity, applying redispatch measures or by the curtailment of generation. The term redispatch is defined by interventions in the generation schedules of conventional power plants to protect power lines from overloading. If a contingency threatens the secure operation of the system, power plants need to reduce their feed-in on one side of the contingency, while plants on the other side have to increase their feed-in capacity. In this way, the resulting PFs do not cause overloading of lines and transformers. Applying redispatch measures lead to costs for the power plant owner since electricity production has to be rescheduled. The curtailment of generation or feed-in management is another regulated, short-term security measure to solve grid congestions. A grid operator may temporarily suspend feed-in from RES and combined heat and power (CHP) plants in his grid, if the grid capacities are not sufficient to transport the total amount of electricity generated. In Germany, electricity from RES and CHP plants have feed-in priority. Feed-in management is, therefore, only used following statutory provisions if the congestion cannot be sufficiently solved by other suitable measures, in particular by regulating conventional power plants (redispatch). If renewable or CHP electricity is regulated by feed-in management, the plant operator is entitled to
compensation from his responsible grid operator. The grid operator, who is responsible for the congestion, has to bear the costs for the redispatch and curtailment measures. These compensation payments can be reimbursed if, for example, an upstream grid operator is responsible for the congestion due to a lack of infrastructure. The responsible grid operator can, in turn, socialize the costs through his network tariffs, provided that the feed-in management was necessary, and he is not responsible for the measure – for example, due to insufficient grid expansion measures [8, 12]. Figure 1.3 shows the increasing operational costs from redispatch and curtailment measures as short-term solutions to the insufficient grid infrastructure.

![Figure 1.3](image_url)

**Figure 1.3:** Annual expenditures from redispatch measures and curtailed energy from RES in Germany from 2007 to 2018 as well as the percentage of RES of gross electricity consumption [11,13–15].

The cost for redispatch measures increased with higher amounts of RES in the power system from €30 million per year (14% RES) up to €423 million with a share of over 36% of RES in 2017. At the same time, the demand for feed-in management measures in 2017 was at its highest level to date with 5.52 TWh of curtailed annual energy. This amount equals 2.4% of the total generation of 225 TWh of electric energy from RES. Compared with the previous year, the resulting costs increased by €237 million to €610 million. In 2018, costs further increased to €635 million. Wind onshore is the most frequently controlled energy source, accounting for 81% of curtailed energy [10].
Chapter 1. Introduction

Remuneration of RES

The calculation of curtailment costs depends on the remuneration mechanism of RES. Various funding mechanisms for RES are implemented by the federal government to reach its target of generating 80% of electricity from RES in 2050. The EEG provides incentives for the installation of RES with lower and higher rated power outputs. Grid operators are obliged to compensate the operators of the EEG plants for feeding the electricity into the grid. The rate of remuneration depends on the installed power, the respective technology, and the location of the generator. In the first version of the EEG of 2000, owners of photovoltaic (PV) generators, wind power plants (WPPs), and other RES received a fixed remuneration for energy fed into the grid. There was no limitation on the size of the distributed generator. With several amendments of the EEG, stricter requirements were introduced to obtain a fixed remuneration. Most importantly, the installed maximum power was gradually limited. Since January 2016, only small power plants with rated power values up to 100 kW receive a fixed price remuneration. For larger power plants, a market premium model was introduced in 2012 to maintain the investment security of a fixed price remuneration. This model aims to reduce entry barriers for direct marketing of the generated power. Until 2017, power plant operators were granted a flat rate allowance for the higher costs resulting from direct marketing in comparison to a fixed remuneration when using the market premium. Since 2017, the market premium is now determined by a bidding procedure of the Federal Network Agency for electricity from RES. The bidding procedures are carried out once or several times a year for each type of RES. In the bidding procedures, the plant operators bid on the value to be invested, which represents the fixed sum of the market premium and the monthly stock exchange revenues. The amount of subsidy is automatically adjusted to the market premium – so that the value to be invested remains constant for the subsidy period [12]. As Fig. 1.4 shows, directly marketed energy from RES constantly rises since 2009. The majority of energy generated from RES is now directly marketed with a share of over 78% of the yearly generated energy.

Investments at the High Voltage Level

The high voltage (HV) level plays an important role in the integration of RES. In Germany, the majority of the installed RES capacity at the HV level, 86.7% (27 GW),
1.1. Motivation

Figure 1.4: Yearly fixed price and direct marketing remuneration of RES energy in Germany between 2009-2017. The given percent values are the share of direct marketing remuneration [5].

are wind power plants. These power plants are fully controllable by the power system operator, which allows considering their operational flexibility in grid planning [5]. HV grids connect the low voltage (LV) and medium voltage (MV) levels with the extra high voltage (EHV) grid and connect rural with urban areas. Even though the majority of RES are installed in the MV grid, studies show that the highest investments are expected in HV grids [16–21]. An additional amount of 12-19% of the total line length (96 300 km) of the HV level must be newly built and 22-26% of must be upgraded until 2030. This results in the highest expenditures of all distribution levels and the sub-transmission level, with 48-61% of the total investments [16]. A similar number of 45% of the total investments of €23-49 billion, depending on the scenario, are expected until 2032 by [17]. These high expenditures can additionally be seen in recently published grid expansion plans of German DSOs [22–24].

There is a high potential to reduce these costs at the HV level by considering operational flexibility in the grid planning process. Since 2016, a change in German law allows integrating operational flexibility in the planning of the power system [12]. Examples of operational flexibility are storage systems, power-to-gas installations, and demand side management. Recent studies show that when distribution and sub-transmission system operators manage to consider operational flexibility in grid planning, it is possible to reduce additional investments from €36.8 billion to €16.8 billion by 2035. This reduction equals a total decrease from 55%-59% or an annual value of €2.15 billion (−42%) [25, 26]. The integration of operational flexibility in planning is a new degree of freedom for power system operators and an alternative investment option to conventional measures.
A Demand for New Planning Strategies

Traditional planning methods are based on worst case assumptions, which only regard very few loading situations and neglect the time dependency of RES, loads, and storage systems. These worst case methods are not able to consider time dependent operational flexibility sufficiently. New power system planning strategies are needed to integrate the time dependency of these assets and thereby their provided operational flexibility. By integrating this operational flexibility in the planning process, it is possible to significantly reduce annual investments [25, 26]. Therefore, power system operators need new methods for planning to find optimal investment decisions considering operational flexibility and conventional measures. Three aspects are substantial for such a method:

1. **Integrated optimization**: Combining the optimization of conventional measures and operational flexibility is needed due to the increasing share of RES. The possibility to control operational flexibility is an alternative investment option to conventional grid measures in power system planning. The expenditures of the operational side and long term investments must be modelled within a combined optimization. This integrated planning method will help power system operators to find an optimal investment decision and to reduce the total expenditures by designing the infrastructure according to future demands.

2. **Time series simulations**: Time series simulations allow to model the time dependency of loads, RES and operational flexibility, such as the curtailment of generation or storage systems. Traditional planning methods, based on worst case assumptions, cannot consider this time dependency sufficiently. Adequate time series models are, therefore, required to simulate operational flexibility in planning to identify and solve critical loading situations.

3. **Fast assessments of contingency cases**: HV systems have high security requirements and are planned with redundancy. The outage of one asset must not lead to a loss in overall supply. Incorporating this additional \(N-1\) security aspect in planning requires further calculations leading to a high computational effort. The automation of the analysis is necessary to handle the complexity of analyzing long time periods and the \(N-1\) aspect simultaneously. A fast method is needed, which is suitable for practical applications. When
implementing the planning method, a trade off must be found between simu-
lation time and model detail.

1.2 State of the Art – Power System Planning

The primary objective of strategic power system planning is to meet future de-
mands and integrate RESs with the restriction of being as reliable, economical, and
environmentally friendly as possible [8]. These requirements result in many differ-
ent optimization targets and planning problem formulations, which can be solved in
multiple ways [27]. Standard industry practice in power system planning of distribu-
tion and sub-transmission grids is to analyze few hypothetical worst case situations
manually [1]. Power system operators utilize software to analyze PF results for
these worst cases or other security aspects, such as $N$-1 contingency cases and
short circuit currents. Grid reinforcement measures are determined by evaluating
different conventional planning options by the grid planner without automation [1].
Planning results depend on the experience of the grid planner, and operational
flexibility is either not considered or taken into account by simple heuristics such
as the federal curtailment factors [28].

1.2.1 Power System Optimization Methods

Researchers solve the different network expansion planning formulations by apply-
ing various optimization methods [29]. They often formulate power system planning
problems as combinatorial optimization problems with a single objective function
that minimizes costs. Boundary conditions to these problems are sets of technical
and operational constraints [30]. These constraints include the PF formulation,
which is non-linear in alternating current (AC) systems. The result are non-convex,
mixed integer non-linear programming (MINLP) problems which are classified as
$NP$-hard [31]. A challenge when solving these problems is that multiple local so-
lutions exist, which are hard to escape by the optimization algorithm [32]. Two
general approaches are widely applied as solution strategies: mathematical programming methods and heuristic optimization strategies, as demonstrated by many review studies [27, 29, 30, 33–38]. The authors of [27] outline that each computational method has its advantages and disadvantages, and that their appropriate use depends on the particular case. Real world power systems are of immense scale, while most existing mathematical optimization strategies have been tested only with small scale systems [35]. Metaheuristics, on the other hand, are often applied in large scale systems. However, the capabilities of these heuristics depend on the dimension and complexity of the problem, which increases with the size of the network [36]. The authors of [33] show that a majority of 57% of models are based on metaheuristic methods, 36% of researchers apply mathematical optimization strategies and only 7% use hybrid methods.

**Metaheuristic Optimization**

Metaheuristic optimization methods are generally easier to implement compared to mathematical programming approaches since no mathematical formulation of the problem is required. Instead, the optimization space is iteratively searched for a solution by systematically evaluating different measure combinations. Heuristic optimization methods are proven to be robust and able to find near-optimal solutions for complex, large-scale planning problems [30]. However, they cannot guarantee to find the global optimum for realistic grid sizes. A well known and often applied metaheuristic for combinatorial optimization is the Genetic Algorithm (GA) [39–41], which is also applied in distribution grid planning for decades [42–44]. Other heuristics, such as the Particle Swarm Optimization (PSO) [45,46], Hill Climbing (HC) [47], or Iterated Local Search (ILS) [48,49] are common applied methods to optimize the grid infrastructure. Newer metaheuristic methods are in development such as the Grey Wolf Optimizer (GWO) [50,51] or the Fireworks Algorithm (FWA) [52,53], which are applied for the optimization of power systems.

**Mathematical Programming**

While metaheuristics repeatedly calculate steady-state AC PFs to find a planning solution, mathematical programming methods work differently. They mini-
mize a particular optimization function, which is constrained by the PF equations as boundary conditions. A solver tries to find a valid assignment of the optimization variables to minimize costs for generation, losses, or grid extension. In recent years, a vast increase in novel mathematical programming methods for formulating and solving these problems is seen in research [54]. Promising results are demonstrated by different relaxation and approximation methods on a wide range of problems, including optimal power flow (OPF) [55, 56], switching state optimization [57, 58], and network expansion planning [59–61]. Mathematical programming methods are common in transmission grid optimization [33] and distribution system planning [30, 62–65]. Formulations range from new PF approximations, which consider reactive power optimization in direct current (DC) PF problems [66, 67], to convex relaxations. Many studies avoid non-linear optimization and use quadratic or linear terms instead of non-linear formulations [34]. Applying this simplification allows employing efficient solving algorithms, which increase the chance of convergence. However, the obtained solution is not guaranteed to be optimal for the non-linear problem. Convex relaxations include semidefinite programming (SDP) [68, 69], quadratic convex (QC) [57], and second order conic (SOC) [70] programming methods, which can find near-optimal solutions and allow employing state-of-the-art convex optimization techniques. Part of the current research is the identification of boundary conditions of the PF [71, 72] and optimal PF problems [73–75]. It is the goal to identify the subset of the non-convex problems where an interior point method always converges to a global optimum [76]. Overviews of different approximation and relaxation schemes are given in [77, 78].

**Hybrid Optimization**

The drawback of non-convergence or non-optimality of the found solution by mathematical programming and metaheuristic methods can partly be solved by combining both methods. Hybrid algorithms allow to solve large expansion planning, multi-stage or multi-objective problems and reduce computational time significantly [37]. Multi-objective planning integrates multiple optimization targets in the planning process. Variable generation and demand can be considered in simulations by using a multi-objective evolutionary strategy for the optimization process [79]. Many hybrid network planning concepts are based on GAs and mathematical optimization methods to overcome local optimum solutions in multi-objective planning [80–83].
Several possible planning schemes are developed for meshed systems [80]. The authors of [81] and [82] demonstrate that hybrid methods can consider network expansion measures and operational flexibility in the same optimization for large AC system models. Their results outline that lower investments are obtained by working directly with the AC model, instead of using relaxations. Hybrid methods show advantages in power systems with a high share of wind generation as demonstrated by [83].

1.2.2 Time-Series-Based Planning

All three optimization approaches allow integrating operational flexibility in the planning process. Heuristic methods often apply simple and generally applicable rules, such as static curtailment factors, whereas mathematical programming models optimize the system with OPF formulations. A large number of OPF formulations exist, which model operational flexibility [84–86] including storage systems [87–89] or markets [90, 91]. These models are commonly sophisticated optimization models, which are designed for short-term optimization. In power system planning, long-term horizons are regarded, which necessitate analyzing multiple scenarios to reduce uncertainty. The sophisticated simulation models are simplified to integrate power system planning and operational flexibility. The influence of detailed models on power market simulations when evaluating operational flexibility is shown in [92].

When integrating operational flexibility in the planning process, time series simulations are required to model time-dependent characteristics. If no or few measurements are available, as it is often the case in MV and LV grids, time series must be artificially generated for the simulation [93]. Methods to generate these time series, as the basis for the planning of distribution grids, are published in [94, 95]. The authors developed a multi agent system to model the independent behaviour of different market participants, including the grid operator, consumers, RES- and storage system owners. Through the interaction of these participants, time series are obtained, which take into account operational restrictions as a basis to find grid planning decisions. The author of [96] focuses on the determination of relevant loading situations from time series and shows how to derive these load cases.
for grid planning at the MV level. In the HV and EHV-levels, historical time series are commonly available from measurements. Depending on the grid operator, these measurements include real- and reactive power values, complex voltages, and currents.

New methods for grid planning including RES, storage systems, and demand side management (DSM) are currently state-of-the-art in research [97–100]. The author of [97] focuses on the interaction of RES and flexible loads in MV grids as a basis for grid planning decisions. The ant-colony optimization metaheuristic is coupled with dynamic programming methods to find investment decisions under consideration of operational flexibility. In [98], an optimization framework for MV grids is described, which applies the Benders decomposition method. The grid planning problem is divided into a master- and sub-problem to find an investment decision including conventional measures and the costs of operational flexibility including RES curtailment, storage systems and DSM. Mathematical programming methods are developed to solve the planning problem. The author of [101] compares different curtailment methods as planning principles in MV grids. The impact of the curtailment of RES in HV grid planning is considered in [102]. A different method for HV grids is published in [100]. The author evaluates different network expansion plans considering operational flexibility and uncertainty with mathematical programming methods based on relevant loading situations.

### 1.2.3 Computational Effort in High Voltage Systems

Additional security aspects and shorter outage times are required in HV systems since more customers are connected to this voltage level [103]. There is an additional need for enhanced contingency planning methods with an increasing amount of cyber and physical threats in smart grids [104]. An important security aspect of reducing outage times and designing a more reliable grid is the consideration of the single contingency policy (SCP) or $N$-1 criterion in grid planning [1]. The SCP is considered in meshed transmission systems [105] as well as in radial distribution systems [106]. The authors of [107, 108] employ heuristic methods to integrate the SCP in planning, while [109] applies an OPF-based optimization method. When
combining the SCP with time-series-based planning, millions of PF calculations have to be performed if multiple years are analyzed. For example, $N \cdot T$ PF calculations are needed to simulate one year in 15 min resolution ($T = 35040$ time steps) for a power system with $N$ lines when the SCP is taken into account. A fast evaluation of the SCP is, therefore, necessary to reduce the overall calculation time [110]. A linearized distribution factor method is applied to integrate the SCP in the simulation in [99]. The author utilizes probabilistic Monte Carlo simulations to obtain different loading situations for HV grids. The necessary curtailment of RES is then determined with mathematical programming methods based on these load cases. Many OPF based optimization methods are tested mostly for small scale-system sizes. The authors of [111] show results for a 13-bus test system. They formulate a mixed integer programming (MIP) problem for transmission expansion planning considering the $N$-1 contingency constraint. In [112] a Benders decomposition method is demonstrated for a 24-bus test system considering $N$-$k$ security analysis. A similar method for $N$-$k$ security is detailed in [113]. The authors apply a Benders decomposition method to solve the problem for larger systems with up to 300 buses. The authors of [114] highlight that the huge number of possible $N$-2 contingencies makes their direct assessment computationally prohibitive. Therefore, fast methods are needed to determine if a grid-state complies with the SCP.

1.2.4 Literature Overview and Research Need

As a summary of the state-of-the-art, it can concluded that most of the methods, which combine the optimization of operational flexibility and conventional grid planning, focus on MV grids. Few strategies are available for meshed HV systems, which sufficiently consider time series simulations and the SCP security policy for large scale systems. An integrated optimization method is needed, which helps power system operators to find investment decisions for several years. The method must evaluate conventional grid planning measures under consideration of operational flexibility. It must be applicable in industry practice, which requires to find a trade off between model complexity and simulation time when taking into account the SCP security aspect. Figure 1.5 shows an overview of the current state-of-the-art in research and identifies the research gap filled by this thesis.
The overview shows that an optimization strategy is needed, which is applicable to realistic sized, large scale systems. A hybrid optimization strategy seems suitable since the advantages of mathematical and heuristic strategies can be combined. Heuristics allow increasing convergence, while mathematical methods provide near optimal solutions. The planning strategy must incorporate time series simulations to model time dependent operational flexibility from storage systems and the curtailment of generation. Since long term planning horizons are regarded, the strategy must be able to consider multiple future scenarios. These future scenarios are uncertain by definition. With limited computational power, a trade off is to be found between modelling detail and simulation time. A fast method is needed to evaluate PF results without a loss in precision. Reducing the calculation time is crucial when the SCP criterion is considered.

Figure 1.5: Venn diagram of the state-of-the-art overview. This thesis fills the research gap of a strategy, which combines time series simulations, considers the SCP, and applies a hybrid strategy of mathematical programming and heuristic optimization methods to be applicable in meshed HV sub-transmission systems.

1.3 Objectives

The objective of this thesis is to develop a power system planning strategy aimed at meshed HV sub-transmission power systems combining the optimization of conventional grid planning measures and operational flexibility control, helping power
system operators to find optimal investment decisions. The strategy is designed for meshed HV systems, which have to fulfil additional security aspects such as the SCP criterion. The following objectives have to be achieved:

1. **Modelling of operational flexibility:** The operation of the power system must be simulated to integrate fluctuating generation and the flexible use of storage systems in the planning stage. In this thesis, simulation models of RES, loads, and storage systems are implemented. These models are the basis for the time series simulation, which allows to sufficiently consider time dependent operational flexibility in the planning process. Simulating the operational measures increases complexity. Therefore, automated analysis of the time series results is needed.

2. **Reduction of simulation time:** Time series simulations require longer simulation times in comparison to worst case planning methods. Long simulation times are a significant drawback in industry applications. Therefore, it is one of the objectives of this thesis to find a trade off between simulation time and model detail. This thesis implements tailored operational models which are suitable for power system planning. To further speed up the simulations, the implementation of the PF algorithm can be optimized for time series simulations. Tailored PF implementations and approximation methods allow reducing calculation time without a significant loss in precision. State-of-the-art machine learning (ML) methods enable to reduce this time by approximating PF results for similar loading situations. Since multiple ML algorithms exist, it is one objective of this thesis to identify the most suitable algorithm to reduce simulation time with a low prediction error.

3. **Optimizing the investment:** Critical loading situations are results of the time series simulations. Several optimization methods exist to solve these loading situations and to find an investment decision. A comparison of heuristic and mathematical programming methods for realistically sized problems is needed. It is the objective of this thesis to identify a suitable strategy that combines the advantages of both methods when regarding operational and conventional planning measures. The question arises if a hybrid optimization method is more suitable to find an investment decision than worst case methods. Furthermore, a strategy is needed, which considers these optimizations
in consecutive, multi-year planning horizons. This thesis develops such a strategy.

4. Evaluation on realistic systems: All implemented models and methods are to be evaluated on realistic and publicly available test systems. Evaluations on publicly available system models allow to reproduce results and compare other methods with the presented approaches. Additionally, a case study on a real grid with measured customer data has to prove the validity of the planning strategy for industry purposes.

1.4 Structure and Contributions of this Thesis

Figure 1.6 depicts an overview of this thesis, which is structured in 6 chapters:

Figure 1.6: Overview of Chapters 1-6. The implemented methods of the sections in Chapter 4 correspond to the results outlined in the sections of Chapter 5.
Problem Analysis: Chapter 2 explains technical and economic requirements for the planning of meshed power systems. The degrees of freedom from operational flexibility and conventional planning in time-series-based planning are described. Furthermore, currently employed planning practices are outlined and compared. Based on this analysis, the requirements for a new planning strategy are formulated.

Existing Methods: Different methods to consider the requirements of modern power system planning are outlined in Chapter 3. First, the pandapower data structure and PF implementation are described as the basis for the developed time series simulation framework. Second, state-of-the-art ML methods are introduced which allow approximating PF results. Third, common optimization methods for combinatorial optimization are described. Finally, the chapter shows the choice of procedure for the following implementation.

Implementation: In Chapter 4, the implementation of planning strategy is detailed. The chapter introduces the time series module, which is integrated into the open-source software pandapower. One focus of this chapter is the approximation method of PF results with ML methods. Results from the time series simulation are the basis for the following optimization. The chapter formulates the optimization problem and introduces a hybrid method to solve the multi-year planning problem for meshed HV power systems.

Validation and Case Studies: Chapter 5 validates the implemented simulation models and methods. Results are shown for four open-source benchmark grids. Additionally, two case studies based on real power system data show the results of the time-series-based planning method. Results are compared to the worst case planning approach to demonstrate the advantages of the time-series-based method.

Conclusions: Conclusion are given in Chapter 6 and results are summarized. Additionally, an outlook on further research needs is identified.
Contributions

Table 1.1 summarizes all contributions of this thesis and related publications of the author.

<table>
<thead>
<tr>
<th>Contribution Summary</th>
<th>Chapters</th>
<th>Further References</th>
</tr>
</thead>
<tbody>
<tr>
<td>The time series module in pandapower - an open-source implementation which is able to consider different controller in a time series simulation.</td>
<td>4.2.1</td>
<td>[115, 116]</td>
</tr>
<tr>
<td>Reduction of overhead in time series simulations to speed-up time series simulations</td>
<td>4.2.2, 5.1.1</td>
<td>[115]</td>
</tr>
<tr>
<td>An efficient implementation of the Newton-Raphson PF method in pandapower</td>
<td>4.2.2, 5.1.1</td>
<td>[117]</td>
</tr>
<tr>
<td>ML methods to predict bus voltage magnitudes and line loadings</td>
<td>4.2.3, 5.1.2</td>
<td>[110, 118–120]</td>
</tr>
<tr>
<td>A multi-year planning strategy for meshed HV systems</td>
<td>4.3.1</td>
<td>[121]</td>
</tr>
<tr>
<td>Operational simulation models including curtailment methods and storage systems.</td>
<td>4.3.2</td>
<td>[122, 123]</td>
</tr>
<tr>
<td>A hybrid optimization method for grid planning</td>
<td>4.3.3, 5.2</td>
<td>[124]</td>
</tr>
<tr>
<td>An evaluation of different optimization methods</td>
<td>5.2.1</td>
<td>[125]</td>
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2 Problem Analysis

In this chapter, the problem of time-series-based power system planning is analyzed. The chapter is divided into four sections. First, the planning requirements for meshed HV sub-transmission systems are outlined in Section 2.1. In this context, specific technical requirements are described. These include topology restrictions, voltage, and line loading limits, as well as the $N-1$ security aspect. Additional economic criteria and methods are explained, which are relevant when determining the cost of conventional measures and operational flexibility in the planning context. In Section 2.2, available degrees of freedom of a grid planner are detailed. These include long term, conventional planning measures such as the replacement of lines or transformers and short term measures from operational flexibility such as the curtailment of generation. Different optimization methods are portrayed in Section 2.3 including the worst case, probabilistic and time-series-based method. As a result of the analysis, the resulting requirements for a new planning strategy are summarized in Section 2.4.

2.1 Planning Criteria of High Voltage Systems

Power systems are divided in the transmission and the distribution levels, which are further separated in different nominal voltage levels. The sub-transmission system is the link between the transmission and distribution levels. In most countries, the sub-transmission level is maintained by a TSO. In Germany, multiple HV sub-transmission systems are operated by different DSOs. The developed methods of this thesis focuses on meshed sub-transmission systems with the following characteristics [1,126]:

---

[1,126]: Reference citations to be added.
• a meshed topology,
• nominal voltages \( \geq 110 \text{kV} \) (HV-level) and \(< 220 \text{kV} \),
• the SCP or \( N-1 \) criterion is fulfilled,
• the typical outage time in case of failures within a millisecond range, and
• full observability with automated switchgear is ensured.

HV systems with nominal voltages \( V_n \geq 110 \text{kV} \) are usually planned and operated as meshed power systems, which are characterized by a complex system structure and higher expenditures for system planning and loading in comparison to radial or open-loop networks as applied in MV or LV grids. Meshed systems are more reliable but have higher requirements on protection devices, automation, and redundancy. Since more customers indirectly connect to the HV level, reliability must be higher and outage times as low as possible. Power system planners of HV systems consider the high-reliability requirements by different measures, e.g., the grid topology (meshed) and the SCP [1].

### 2.1.1 Technical Requirements

Meshed topologies are most often applied in systems with a high load density. Therefore, they are used at voltage levels \( \geq 110 \text{kV} \) at the HV- and EHV-levels. Meshed systems have a rather complicated system structure in comparison to radial or open-loop topologies. HV protection is based on distance protection relays or with differential protection instead of simpler overcurrent protection relays. The loading of lines during normal operation is less than 100\% of the thermal limits to include a security margin in case of failures. Power system operators define their planning criteria and the reserve for outages individually. Meshed systems are operated with all breakers closed under normal operating conditions, which leads to lower voltage deviations, in comparison to radial networks, under normal operating conditions and in case of outages. Another advantage is that meshed systems are highly flexible due to different possible switching states in changed loading conditions. The higher redundancy ensures a lower number of interruptions of supply. However, this results in higher expenditures for system planning.
due to a higher number of power lines, transformers, protection, and the cost of maintenance. In most systems, standardization of cross-section and rating of the equipment is aimed at [1, 127]. Figure 2.1 exemplarily shows the difference between a radial, open-loop, and a meshed grid topology. This thesis focuses on meshed systems as shown in Figure 2.1 c).

Figure 2.1: Grid topologies: (a) radial network; (b) open-loop; (c) meshed system (adapted from [127]).

SCP or $N$-1 Criterion

HV system planning criteria demand that an outage of any equipment, e.g., overhead lines, cables, transformers, compensation, or busbar sections, will not cause a loss of supply to any load. These outages increase the loading of the remaining equipment and are accepted for a specified period. Additionally, the voltage profile will worsen during the outage. In live operation, system operators have to rearrange the system, e.g., to change the switching state, to reduce equipment loading, and improve the voltage profile. Depending on the planning criteria for a specific system, single outages ($N$-1)-criterion or multiple outages ($N$-$k$)-criterion are allowed without loss of supply [1]. An example of $N$-1 states is shown in Fig. 2.2. For a system with 13 buses, 12 additional system states have to be evaluated to determine compliance with voltage and thermal limits in the contingency case. This leads to an $N$-times higher computational effort when planning the grid and in live operation.
2.1. Planning Criteria of High Voltage Systems

Figure 2.2: Possible N-1 states in an exemplary 13-bus meshed system. In this example, 12 additional system states have to be evaluated to determine compliance with the technical limits.

Voltage Limits

Power system operators individually define voltage tolerances in normal and contingency cases for the planning of the system. Typically, operators derive these limits from standards such as the IEC 60038 [128]. For HV systems, the IEC 60038 specifies the nominal voltage $V_n$ and the highest voltage for equipment $V_m$. In Germany, these values are $V_n = 110\,\text{kV}$ and $V_m = 123\,\text{kV}$. The standard defines no criteria for voltage tolerances at the HV-level. Instead, system operators specify these tolerances in coordination with the subordinate grid operators. For HV systems, [1] recommends a tolerance band of $\pm 5\%$ in relation to $V_n$ during normal operation. Voltage deviations are reduced by automatic tap-changers of the feeding transformers or other measures, e.g., generator voltage control, reactive power compensation equipment. In the case of a single outage without switching or corrective measures, it is recommended to keep the voltage within a tolerance of $\pm 10\% \cdot V_n$ in HV systems. With corrective measures, e.g., by operating the tap-changer of feeding transformers or redispatch of generation, the voltage is to be kept within a tolerance of $\pm 8\% \cdot V_n$ in HV systems [1].

Loading Limits

Permissible loading criteria of equipment, such as power lines or transformer, are defined under normal operating conditions (long term ratings) and for single outage
or multiple outages (short term ratings) by standards, regulations, and data sheets of manufacturers [1]. A common standard for power line and cable ratings under normal operational conditions is the DIN 50182 [129]. In general, the cross-section and material of power lines define their thermal limits. These values are given for a maximum operating temperature of, e.g., $\vartheta_{\text{max}} = 90^\circ C$. The rated currents $I_r$ for common standard type HV overhead lines (e.g. 184-AL1/30-ST1A) or HV cables (e.g. N2XS2Y 1x240 RM/35 64/110kV) range between $I_r = 0.4 - 1.0 \, kA$. In the case of outages, the loading of the equipment remaining in operation may not exceed the values defined for a given period as specified for the respective equipment. Short term ratings for short-circuit cases are given and higher temperatures are allowed, e.g., $\vartheta_{\text{max}} = 250^\circ C$ [126].

### 2.1.2 Economic Criteria

Power systems are designed for long term operation. The equipment is in operation for several decades. Power system operators must consider CAPEX and OPEX when deciding whether to invest in the installation of new equipment or not. CAPEX, depend on the installed power and, therefore, on the voltage level of the installed assets. Examples are costs of installed/upgraded primary equipment, e.g., lines, transformers, busbars, and secondary equipment such as protection devices. In the past, OPEX mainly resulted from PFs and corresponding losses in the system. This has changed with the gradual reduction of nuclear and fossil energy plants and an increase in electricity feed-in from RES at the same time. With the rising share of RES, further OPEX, such as the cost of RES curtailment, redispatch, and other operational flexibility, have to be taken into account.

For a proper long term integration of RES, power system operators must consider operational flexibility when planning the grid. Methods are needed to find an investment decision considering operational measures and conventional measures. Costs from operational measures are accounted for annually, whereas costs from conventional measures are result in immediate investments. These investments are often financed by debt capital, being depreciated over many years. A standard method is to depreciate the investments with the annuity method. This allows an
integrated optimization and comparison of CAPEX and OPEX in the planning of the system.

**Annuity Method**

Power system infrastructure, such as power lines, transformers, or substation equipment, are utilized over many decades. The annuity method can be used to find an investment decision in a new project and to be able to compare resulting CAPEX with annual OPEX. The annuity of a project is calculated to finance the installation expenses, costs of losses, and flexibilities as well as the required sales. The method is appropriate if costs are continuous over the time period. The annuity $A$ is calculated as:

$$A = K_0 \cdot (a_n + C_{all}) + C_s \quad \text{with} \quad a_n = \frac{q^n \cdot (q - 1)}{q^n - 1}$$  \hspace{1cm} (2.1)

The annuity consists of the acquisition cost $K_0$ multiplied with the annuity factor $a_n$ and a fixed percentage $C_{all}$ of the annual OPEX for the asset. The annuity factor is calculated by the interest factor $q = i_r + 1$ with a given interest rate $i_r$ and the depreciation years $n$ of the asset. $C_{all}$ results from different costs such as maintenance, administration, taxes, and insurance. A standard value for $C_{all}$ is $0.5 - 1.0\%$ of $K_0$. Additionally, the energy-dependent, consumption-related costs $C_s$ are added as a fixed value [130]. In this thesis, the following investments are considered in the planning strategy with the annuity method:

- replacement of existing power lines (cables and overhead lines),
- installation of new power lines, and
- upgrading of transformers.

Other necessary investments, such as information and communication technology (ICT) and measurement infrastructure, are not regarded. Figure 2.3 (a) depicts the annuity method with $C_{all} = 0$ and $C_s = 0$. The initial investment $K_0$ in year zero is divided into equal payments of $A$ for the next $n$ years with the annuity factor $a_n$. 
Discounted Cash Flow

The discounted cash flow (DCF) is an investment method for determining the value of investment projects. It is based on the financial mathematical concept of discounting cash flows to determine the present capital value. The DCF method discounts future cash flows to a given valuation date. The net present value (NPV) calculated in this way is the discounted cash flow \( C_0 \). The NPV for a given interest rate \( i \) is obtained by sum of the discounted cash flows \( C_t \) of each period \( t \) [131]:

\[
C_0(i) = \sum_{t=1}^{T} \frac{C_t}{(1 + i_r)^t}
\]  

(2.2)

In this thesis, the DCF method is applied to obtain the NPV resulting from cash flows of operational measures (OPEX) and the annuity values of CAPEX as defined above. Figure 2.3 (b) shows the discounted cash flow method. The cash flows \( C_1 \) to \( C_n \) are discounted with the interest rate \( i_r \) to obtain the NPV \( C_0 \) in year zero.

![Figure 2.3: (a) Annuity Method and (B) Discounted Cash Flow](121).

Curtailment Costs

The German law states that power system operators must compensate owners of RES, mine gas or CHP plants for at least 95% of lost revenues due to a curtailment of generated electricity in cases of grid congestions. If the lost revenue exceeds 1% of the revenue for a given year, the operators affected by the curtailment must
be compensated 100% [12, 132]. The remuneration of the electricity generated by RES depends on its type, installed capacity and if it is directly marketed or not (see Fig. 1.4 in Section 1.1). When calculating the costs of curtailment, RES being remunerated by feed-in tariffs are treated differently to directly marketed power plants [132]:

**Feed-in tariff:** All payments according to the EEG that the plant operator would have received for the electricity that he was unable to feed into the grid due to curtailment measures are recorded as lost revenue. In the case of RES, these revenues essentially involve the feed-in tariffs as regulated by the EEG.

**Directly marketed:** If the electricity generated by the plant is sold by way of direct marketing with a market premium, only the market premium is taken into account as lost revenue, since the sales proceeds can be achieved independently of the curtailment measure. In the case of direct marketing without a market premium, only the avoided grid fees without the curtailment measure must be compensated as lost revenue.

At the HV level, WPPs account for the largest share of RES. Over 95% of the energy generated by these power plants is directly marketed [5]. Since 2017, the market premium is determined by a bidding procedure of the Federal Network Agency for electricity from RES as explained in Section 1.1.

**Costs from Redispatch**

In Germany, electricity from RES and CHP plants have feed-in priority. Curtailment is, therefore, only applied following if the congestion cannot be sufficiently solved by other suitable measures, in particular by regulating conventional power plants in the area of the power system operator (redispatch). Redispatch is an intervention in the generation schedules of conventional power plants to protect power lines from overloading. In the case of contingencies, power plants reduce their feed-in on one side of the contingency, while plants on the other side have to increase their feed-in capacity. Redispatch helps to avoid power line and transformer overloading. The application of redispatch measures leads to costs for the power plant owner since electricity production has to be rescheduled.
Costs from Operational Losses

Losses are determined by the current flowing through an asset, which leads to stress in the material and to aging effects. The loading is determined by impedance and voltage difference between two points and the duration of the loading. Different types of losses exist, including thermal losses, voltage-dependent losses, and compensation losses. Thermal losses in equipment such as lines and power transformers are load sensitive and current dependent. These are mainly ohmic losses, which are proportional to $I^2$. Voltage-dependent losses are load insensitive and are proportional in the first approximation to the square of the operating voltage. They occur in transformers and electrical machines, result from the corona of overhead lines and insulation losses and dielectric losses in cables, transformers, insulator defects, or dirt. Compensation losses are mostly relevant for HV and EHV AC systems and result from reactive power compensation equipment such as induction coils [1].

2.2 Planning Measures

This section details conventional planning measures and operational measures applied in power systems. Traditional power system planning is based on conventional measures as explained in Section 2.2.1. Common operational measures are detailed in Section 2.2.2.

2.2.1 Conventional Measures

Distribution grid planning involves changing the existing infrastructure for a given future supply task, including the integration of RES or an increase in consumption. A grid planner has to design a target grid with several degrees of freedom determined by the conventional measures. These include the installation of parallel power lines, upgrading these, the installation of additional power lines between substations, upgrading existing transformers, and the installation of parallel ones. Figure 2.4 depicts the measures regarded in this thesis for an exemplary meshed grid.
2.2. Planning Measures

The main task of a power transformer, commonly referred to as transformer, is to transform the voltage in such a way that the electrical power can be transported or distributed with the lowest costs possible. Transformers convert power with very low losses; for large units from approx. 200 MVA upwards, the efficiency is around 99.5%. Two-winding and three-winding designs are most frequently used [126]. The most important characteristic values of a transformer are, apart from the voltages on the primary and secondary side, the nominal power in MVA, the short-circuit voltage \( v_k \) given in percent, and the switch group. The higher the voltage level, the higher is the installed power. Typical nominal values in meshed systems range from 40-63 MVA (110/10 kV). A higher redundancy is achieved with parallel installation of the same transformer type. The relative short-circuit voltage is the ratio between the short-circuit voltage \( V_k \) and the nominal voltage \( V_n \) of the transformer \( v_k = \frac{V_k}{V_n} \). It is given as a percentage value. The switching group is codified as a string, e.g., \( Yy0 \), which describes the wiring on the primary (capital letter) and secondary (lowercase letter) side as well as the angle in multiples of 30°. The most common transformer types are two- and three-winding transformers [126]. A power system operator considers these values when upgrading a transformer within a substation or parallel transformers are installed. Technical limits are evaluated by PF and short-circuit analysis.

**Figure 2.4:** Conventional grid planning measures in meshed systems.

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**Power Transformer**

The main task of a power transformer, commonly referred to as transformer, is to transform the voltage in such a way that the electrical power can be transported or distributed with the lowest costs possible. Transformers convert power with very low losses; for large units from approx. 200 MVA upwards, the efficiency is around 99.5%. Two-winding and three-winding designs are most frequently used [126]. The most important characteristic values of a transformer are, apart from the voltages on the primary and secondary side, the nominal power in MVA, the short-circuit voltage \( v_k \) given in percent, and the switch group. The higher the voltage level, the higher is the installed power. Typical nominal values in meshed systems range from 40-63 MVA (110/10 kV). A higher redundancy is achieved with parallel installation of the same transformer type. The relative short-circuit voltage is the ratio between the short-circuit voltage \( V_k \) and the nominal voltage \( V_n \) of the transformer \( v_k = \frac{V_k}{V_n} \). It is given as a percentage value. The switching group is codified as a string, e.g., \( Yy0 \), which describes the wiring on the primary (capital letter) and secondary (lowercase letter) side as well as the angle in multiples of 30°. The most common transformer types are two- and three-winding transformers [126]. A power system operator considers these values when upgrading a transformer within a substation or parallel transformers are installed. Technical limits are evaluated by PF and short-circuit analysis.
Power Lines

Overhead lines and cables transport electrical energy. In higher voltage levels, the amount of cables decreases in comparison to lower voltage levels. The reason is a higher requirement for thermal and electrical insulation for cables on higher voltages. At the 110 kV level less than 10% of installed power lines are cables in Germany. This amount is even less at the EHV level, with only 0.3% [126]. Overhead lines are, however, not favored by the population due to aesthetic and environmental reasons. When installing new lines or upgrading existing ones, the installation of cables is often preferred. The Energy Line Extension Act (ger. Energieleitungsausbaugesetz (EnLAG)) fosters projects based on cables instead of overhead lines [133]. Similar to transformer installations, PF studies and short-circuit analysis determine if the new installation complies with the technical limits.

Other Measures

Other planning measures include the building of additional substations and the installation of stationary reactive power compensation for voltage stability. These measures are out of scope of this thesis. In countries where there is no separation between the power system operator and the utility company, the integrated operator is allowed to place distributed generators (DGs) in the system. This is commonly known as the DG placement problem, which is not targeted in this thesis as well.

2.2.2 Operational Flexibility

Power system operators have several options to mitigate voltage violations and to avoid exceeding thermal limits of line or transformer loading in live operation. They can directly control the on-load tap-changer of power transformers and change the switching state to control PFs. The power system operator can influence consumption by DSM and generation by redispatch measures or the curtailment of generation. Storage systems provide further flexibility. Additionally, RES and storage systems can provide ancillary services in the form of reactive power compensation.
Figure 2.5 shows an overview of different operational measures applied in live operation. All of these measures require an ICT infrastructure to enable the communication between the control center and the controlled entity.

![Figure 2.5: Overview of operational measures to mitigate voltage violations and exceeding thermal limits.](image)

As of today, operational flexibility is considered to a limited extent in power system planning. Since the design of the power system is based on a few worst case assumptions, the flexibility is regarded only for these cases. Integrating time series simulation in planning allows a detailed analysis of the ancillary services provided by operational flexibility. Table 2.1 lists the current and future applications of possible operational flexibilities. In this section, several operational flexibility measures are described. These include conventional measures, such as on load transformer tap-changer or switching state optimization, as well as the flexibility provided by RES, storage systems or DSM.

**On Load Transformer Tap-Changer**

Changing the transformer tap position changes the voltage magnitude setpoint, often at the HV side, of a transformer. In live operation, this reduces voltage deviations from the nominal voltage and is an immediate corrective measure in contingency cases. The direct voltage control with transformers is realized by dividing one of the windings in a main winding and a step winding, which are connected in
Table 2.1: Overview of operational flexibility measures in power system planning today and future possibilities with time series simulations.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Current Application</th>
<th>Time-Series-based Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>On Load Transformer Tap-Changer</td>
<td>worst case assumption</td>
<td>variable adjustment within the simulation</td>
</tr>
<tr>
<td>Switching State Optimization</td>
<td>worst case assumption</td>
<td>variable adjustment within the simulation</td>
</tr>
<tr>
<td>Curtailment of Generation Storage Systems</td>
<td>general scaling factor</td>
<td>dynamic curtailment</td>
</tr>
<tr>
<td>Reactive Power Compensation</td>
<td>worst case assumption</td>
<td>variable utilization</td>
</tr>
<tr>
<td>Demand Side Management</td>
<td>not considered</td>
<td>dynamic provision by inverters</td>
</tr>
</tbody>
</table>

series. The step winding is often further divided into a precise step and a coarse step winding. The difference between the two windings is that the step winding has a tap-changer attached. A tap-changer is a switch that sets a different winding tap in live operation. The tap-changer is either controlled automatically or manually. Depending on the relative short-circuit voltage $v_k$, the range can be up to $\pm 22\%$ of the rated ratio. Typically, a maximum of $\pm 13$ taps are provided for large control ranges [126]. In power system planning today, on load tap-changer positions are evaluated for the assumed worst case situations. Several positions can be tested for the worst case situations to ensure that the bus voltage values are within their limits. Time series simulations allow to dynamically change the tap-positions during the simulation, allowing to evaluate if voltage limits violations can be mitigated by applying tap-changing measures in live operation.

**Switching State Optimization**

The change of the switching position in a grid changes the PFs so that loading and voltage violations are mitigated. An automatic change of switching position is an immediate security measure in contingency cases at the HV and EHV voltage level. In medium and LV grids, DSOs try to maintain a radial or open-loop topology when changing the switching position. In comparison, there are no topology restrictions in meshed systems. Figure 2.6 shows an example of two states in a
fixed generation and loading situation. Line loading limits of the bottom feeder are violated in the single-loop configuration in Fig. 2.6 (a). By closing one switch, the line overloading problems of the bottom feeder is solved in Fig. 2.6 (b). In worst case power system planning, several switching states are evaluated for these situations and a normal switching state is defined. Time-series-based planning allows to dynamically adjust the switching state within the simulation to identify suitable positions for different operational conditions. These states can then be applied in live operation to mitigate voltage or line loading limit violations or to minimize losses. An extended identification of suitable switching states is thereby possible with time series simulations.

![Diagram](image.png)

**Figure 2.6:** (a) Single-loop topology, (b) meshed topology. Changing the switching state in a power system allows mitigating over loadings and voltage problems.

### Curtailment of Generation

General planning principles demand that the power system is designed to enable the connection of all generating power plants at their rated capacity. Since PV and WPP are only operated at their nominal capacity for a few hours a year, potential cost savings can be achieved when considering curtailment of generation in grid expansion planning. According to several studies is “a regulation of a small percentage of the annual feed-in of renewable energy plants sufficient to significantly reduce the expansion of the grid” [16–19]. The authors of [17] state that the inclusion of 3% of the annual feed-in of wind energy and PV generation plants in the grid planning allows to halve necessary grid expansion. The integration of curtailment measures in power system planning was, therefore, legalized by a change in
law in 2016. Since then, grid operators are allowed to consider curtailment of up to 3\%, of the annual generated energy by solar or on-shore wind power plants [8]. A requirement to integrate curtailment in planning strategies is that the power plants are directly or indirectly controllable by the system operator. Figure 2.7 depicts the installed power of RES by type and the share of controllability in 2018 in Germany. Solar power is dominant at the low and MV level. At the HV and EHV levels, the majority of installed power is from wind energy power plants, which are fully controllable.

![Figure 2.7](image-url) (a) Installed power of RES, (b) controllable percentage in Germany in 2017 [5].

The technical regulator for power grids in Germany, VDE|FNN, recommends different concepts to implement curtailment for PV and wind power plants in power system planning [28]. The applicability of these principles depends on the availability of a grid model, time series measurements, and simulation models. These concepts include:

- **General scaling factor**: The incorporation of a general, fixed curtailment factor in power system planning is the simplest recommended method and applied in worst case planning. It requires only that the grid operator has a power system model that includes information on the installed RES and connected loads. Additionally, the relevant peak load cases must be defined, e.g., high load without feed-in or high feed-in and low load (see Section 2.3). If these requirements are met, the curtailment of generation is considered by adjusting the nominal installed power in the simulation by $0.7 \cdot P_N$ for PV and $0.87 \cdot P_N$ for WPPs.
• **Static curtailment:** In comparison to the general scaling factors, individual reduction factors are obtained for each generator in the static curtailment method. Measured time series of WPP and PV plants are needed to determine these reduction factors. These time series are sorted first to obtain an annual duration curve. From this curve, the design relevant, minimum feed-in power (the cap limit), is then iteratively calculated. The minimum feed-in power is the power that is required to curtail no more than 3% of the annually generated energy. The static curtailment method can be applied in worst case planning, if historical time series are available, as well as in time-series-based planning.

• **Dynamic curtailment:** The first step of the dynamic curtailment is to run a PF or $N-1$ study for the power system under consideration. For this, a time series simulation identifies situations with violated technical boundary conditions considering voltage limits and max. allowed PFs. In the second step, the simulated power reduction of the DGs is determined by an OPF calculation. The dynamic curtailment method is the most sophisticated, requiring not only the grid data and time series but additionally an optimization model. The method is, therefore, only applicable in time series simulations and used in this thesis.

**Storage Systems**

Storage systems allow to balance fluctuating renewable generation and demand but may also worsen problems in the power system. Their application in the power system depends on ownership, operational schedules, and possible conflicting interests. If a large number of storage systems charge or discharge simultaneously, e.g., a fleet of electric cars driven by a market price signal, line or transformer overloading may occur. These problems are mitigated by rescheduling charging and discharging cycles with regard to the power system. Storage systems allow reducing overloading and voltage problems if these cycles are synchronized with RES generation. Stationary installed batteries or power to gas installations, however, allow using a surplus of generated energy without the need for curtailment. With an 80-100% share of RES, as planned in Germany for 2050, a much
higher share of storage systems as currently installed is needed [7]. At the distribution level, different types of storage systems emerge with an increasing amount of distributed generators. When regarding the HV level, the most relevant types are:

- **Stationary batteries:** Stationary batteries are installed to provide operational flexibility for the power system operator. Different technologies are used in industrial applications, including sodium-sulfur (NaS), lead-sulfur (PbS), lithium-ion (Li-Ion) or Redox-Flow batteries. All of these technologies have different advantages and drawbacks. Li-Ion and NaS batteries have four times higher energy density of $100-120 \, \text{Wh kg}^{-1}$ in comparison to PbS and Redox-Flow with $20-50 \, \text{Wh kg}^{-1}$. The Li-Ion battery has the highest efficiency rate of up to 95% in comparison to 80-90% (PbS) or less than 80% of NaS and Redox-Flow batteries [7].

- **Power to gas or X installations:** A surplus of renewable generated energy can be converted to gas, e.g., hydrogen or methane, or other power fuels such as synthetic kerosene [134]. This conversion allows long term storage of electricity, which can be recovered via gas-fired power plants, turbines, and CHPs. Additionally, the transport of energy via the gas grid is possible, which relieves the electricity grid. Furthermore, the provision of system services to stabilize the electricity system and the coupling of the electricity sector with the heat sector can be achieved with this technology. This allows integrating renewable energy outside the electricity system or grid. Since 2012, an increasing number of larger capacity classes between 1 and 6 MW went into operation in Germany. These are connected to the MV level and built together with wind parks. Efficiency values range from 60-80% [135].

In worst case planning, storage system outputs can only be considered to a limited extent. Either their minimum or maximum output defines the impact on the planning result. In comparison, time series simulations allow to model charging and discharging cycles of storage systems to analyze their operational flexibility in power system planning. With sophisticated storage simulation and optimization models, ancillary services provided by storage systems can be evaluated in planning. Depending on ownership, intended operational schedules, and a possible conflict in interests, several operational modes must be modelled.
2.2. Planning Measures

Reactive Power Compensation

Power factor correction, also known as reactive power compensation, reduces the undesired displacement of reactive power and the associated reactive current of electrical consumers in AC voltage systems. Power factor correction is achieved by compensating inductive or capacitive reactive power through capacitive or inductive loads. In transmission and sub-transmission systems, compensation is realized with capacitors or compound coils. The generator of modern WPPs or inverters of PV plants are decoupled from the grid via a DC link. In this way, it is possible to control the phase shift between voltage and current in the three-phase alternating current (three-phase current) fed into the grid. These systems can, therefore, be used for reactive power compensation. Reactive power compensation is able to mitigate voltage deviations. OPF methods are commonly applied to integrate reactive power constraints in the planning of power systems [136, 137]. Today, reactive power compensation is considered under worst case assumptions in planning. With time series simulation, it is possible to dynamically adjust the reactive power provision by simulated controllable inverters allowing to evaluate if the provided flexibility is able to mitigate voltage violations in live operation.

Demand Side Management

DSM allows shifting energy from times of high consumption to times of peak generation. An example of DSM is the shift of production processes of industry customers at the HV or EHV level. Industrial production processes provide demand-response in the form of operating reserve. Common types are the cement industry, aluminum electrolysis, the paper industry, and chlorine electrolysis. Currently, the provided power range is between 0.5-1.5 GW in Germany and is offered to a large extent as positive operation reserve for several minutes. The full technical potential is not raised to its full extent. Due to the optimized process chain of the manufacturing industry, however, it can be assumed that the technical potential is much lower than the theoretical one, especially as the economic incentive is very low at the current price level on the operating reserve market. The consequences of load shifting or load shedding for the production process represent a higher price risk than the additional ICT costs for flexibility [138]. DSM is not further targeted in this thesis.
Grid Equivalents

HV power systems are mostly sub-transmission networks being connected to the EHV-level or interconnected by tie lines to HV-systems operated by different grid operators. These external power system areas are typically represented by reduced network models to perform power system analysis in the regarded area. There are two main reasons why the remaining areas are not included in the analysis: First, a limited computational power for large-scale power systems. Second, the interconnected areas are operated by different power system operators, which are not able to share their power system data due to confidentiality [139]. In this thesis, the external grid areas are modelled either as a conventional Ward equivalent [140], an extended Ward as implemented in [116], or as a slack bus with a fixed voltage setpoint. This voltage setpoint may change within a time series simulation, which is considered by a measured time series provided as input data to the simulation. Alternatively, the voltage setpoint can be optimized within OPF calculations by defining voltage magnitude and angle limits.

2.3 Power System Planning Concepts

The technical requirements (see Section 2.1.1) demand compliance with voltage limits and that equipment, e.g., power lines and transformers, do not exceed their loading limits during normal operation and in case of outages. In industry and research, different methods are regarded for the planning of power systems. These methods include:

- worst case planning,
- probabilistic based planning, and
- time-series-based planning.

Worst Case Planning

If time series measurements are not available, operational constraints are evaluated by PF calculations for assumed worst case operating points. This approach
is standard practice at the medium and LV levels [49], and also at the HV level. With the rising share of RES, at least two of these assumed worst grid states are analyzed in target grid planning: a peak load and a peak generation case. As the name states, power system operators assume a high consumption with simultaneously low generation in the peak-load case and, vice versa, a high generation and low loading situation in the peak-generation case. In a simulation, these two worst case operating points are obtained by scaling the peak power values of load and generator elements. System operators obtain these peak values for loads from historical data such as drag-pointer or time series measurements. For generators, they use the nominal installed power values. Exemplary scaling factors are given in Table 2.2. These scaling factors of PV and WPPs depend on the simultaneity of generation resulting from, e.g., different orientations of the modules of PV plants [16]. For the peak generation case, lower transformer voltage setpoints are assumed as for the peak load case. A transformer tap-changer regulates the setpoint in live operation. An example of these peak-cases is shown in Fig. 2.8.

<table>
<thead>
<tr>
<th>Table 2.2: Common scaling factors and tap changer setpoints of worst case assumptions [16].</th>
</tr>
</thead>
<tbody>
<tr>
<td>scaling load</td>
</tr>
<tr>
<td>peak load</td>
</tr>
<tr>
<td>peak generation</td>
</tr>
</tbody>
</table>

The worst case method has several advantages. First, it is simple since only two loading situations have to be analyzed. A power system planner can assess if limits are within their tolerance for both cases manually. Therefore, less automation is required when evaluating different planning options because of the low complexity when regarding few cases. Another advantage is the high security margin resulting from a strong dimensioning of assets since the assumed worst case may never occur in reality. The high margin is, however, also a drawback since real grid states are not regarded and high expenditures may result. In meshed grids, critical loading situations, resulting from mixed load and generation, might lead to higher
loadings or voltage deviations than in the assumed worst cases. Another disadvantage is apparent when a high share of RES is installed in a power system. For a limited geographic region, as it is the case in distribution systems, the simultaneity of feed-in leads to high loadings and voltage deviations. Operational flexibility usage can mitigate this problem. If this flexibility is not considered, as with the worst case method, the result is an over-sized system leading to high investments in the infrastructure.

Probabilistic Planning

The probabilistic PF method is a technique that analyzes the PF problem probabilistically instead of using deterministic methods. Nodal loads and generation are defined as random variables, and the PF in each line is computed as a probability density function [141]. These random values are often generated by Monte-Carlo methods, as in [99]. The expected value and the standard deviation of each PF are calculated. Additionally, the overall balance of power in the system can be determined in terms of a density function. The purpose of a probabilistic analysis is to reduce errors and statistical variations in the operation and planning of systems. This allows a quantitative assessment of reliability and security of a power system [142]. This probabilistic method is used in power system expansion planning, e.g., in [143]. The concept is depicted in Fig. 2.9. From randomly scaled load and generation scalings, the distribution of voltages and loadings are obtained. These distributions are the basis for planning.

The probabilistic PF method calculates the frequency distribution of node voltages
2.3. Power System Planning Concepts

Figure 2.9: Probabilistic power system planning concept. Voltage and loading distributions are obtained by randomly scaling load and generation inputs.

or line currents. In comparison to the worst case approach, the power system planner has more information on the frequency of occurrence of extreme values with the probabilistic method. The advantage is that multiple load and generation cases considered in planning including the extreme cases. However, there is no time depended relationship between individual node voltages or line currents. Without time dependency, operational flexibility cannot be integrated adequately in the planning process. Another disadvantage of probabilistic methods is the high number of required random-samples leading to long simulation times.

Time-Series-Based Planning

Quasi-static time series simulations of power systems allow time dependent modeling of consumption, generation, or markets. In time-series-based planning, time horizons of one or multiple years are analyzed. The time series resolution mostly depends on measurement intervals. Common data sets are available in different time resolutions including $1\text{ h}$, $15\text{ min}$ and $5\text{ min}$ [144–146]. Higher resolutions allow to model operational strategies in detail but have the drawback of a higher computational burden.

Time-series-based analysis allows designing the grid according to the expected needs. The grid is planned for the real demand instead of hypothetical extreme cases from worst or probabilistic assumptions. Therefore, the risk of over-dimensioning is unlikely. However, the time series may not include relevant but rare extreme
Chapter 2. Problem Analysis

cases. Since consecutive time steps are analyzed, time dependent control strategies can be considered in the simulation. Time series analysis allows integrating operational flexibility in the planning process. Additionally, a comparison of different operational models and their impact in the context of grid planning becomes possible. Furthermore, grid operators can determine other kinds of energy-related performance metrics with time series simulations, e.g., system losses. Figure 2.10 shows an exemplary time series analysis. Inputs are time series from measurements, e.g., the real power demand of loads and generation time series from wind and PV power plants. Outputs are bus voltages and line or transformers loadings over time. Additionally, distributions of these values can be obtained.

Figure 2.10: Time series analysis concept. Voltage and loading distributions and results over time are obtained from time series simulations.

A significant drawback of time series simulations is the requirement of adequate time series data as inputs. These can be provided in the form of measured, synthetic, or generic data. In HV and EHV systems, measured P, Q, and V values at substations are commonly available. In lower voltage levels, in the medium and low-voltage grid, an insufficient amount of measured data is available. Here, synthetically generated data can be used as in [93–95]. Alternatively, researchers commonly use generic data from standard load profiles [147] or publicly available data sources such as [144]. The greatest disadvantage of the time-series-based method is the high computational effort when using sophisticated control models or when multiple years are simulated. Analyzing $N$-1 security aspects further in-
creases simulation time. The level of complexity and simulation time is highest in
time-series-based planning compared to the remaining methods.

Comparison

Table 2.3 compares the different planning methods. The advantage of the worst
case method is that it requires the lowest calculation effort. A grid planner must
only analyze a few load cases, which reduces the complexity to a minimum. The
method requires no time series as inputs, which makes it applicable in LV and MV
grids. In comparison, the calculation effort is higher for probabilistic methods since
it analyzes multiple, randomly generated load cases. The extended analysis of
the probabilistic method increases complexity for the grid planner but allows him
to assess loading distributions. Probabilistic methods do not require time series
as input data. Both methods, however, do not allow to integrate operational flex-
ibility to its full extent in the planning of the power system. No time dependency
and, therefore, energy-related operational strategies can be regarded with prob-
abilistic and worst case methods. The integration of operational flexibility in the
planning process is only possible with time series simulations. Their drawback is a
higher calculation effort and assessment complexity. Grid planners need strategies
that reduce simulation times and filter relevant information from the simulation of
longer periods such as years. Time series methods allow to reduce investments
in the infrastructure by taking into account operational flexibility. The system is de-
signed according to its needs without over-dimensioning by unnecessary security
margins. A requirement for time series strategies are available time series as input
data. These can be derived from measurements, which are only available at higher
voltage levels, or generated by synthetic methods.

2.4 Resulting Requirements for a Time-Series-Based
Planning Strategy

With the integration of RES in the power system, new investment alternatives
emerge resulting from the time dependent behavior of DGs, loads, and storage sys-
tems. The conventional worst case planning method and probabilistic approaches
Table 2.3: Comparison of power system planning strategies (++ advantage, – disadvantage, +/- draw).

<table>
<thead>
<tr>
<th>method</th>
<th>worst case</th>
<th>probabilistic</th>
<th>time series</th>
</tr>
</thead>
<tbody>
<tr>
<td>low calculation effort</td>
<td>++</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>low complexity</td>
<td>++</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>simulation of time dependency</td>
<td>–</td>
<td>–</td>
<td>++</td>
</tr>
<tr>
<td>integration of operational flexibility</td>
<td>–</td>
<td>–</td>
<td>++</td>
</tr>
<tr>
<td>lower cost without over-sizing</td>
<td>–</td>
<td>+/-</td>
<td>++</td>
</tr>
<tr>
<td>calculation of loss-energy</td>
<td>–</td>
<td>–</td>
<td>++</td>
</tr>
<tr>
<td>no time series inputs required</td>
<td>++</td>
<td>++</td>
<td>–</td>
</tr>
</tbody>
</table>

New planning strategies are necessary, which consider conventional measures and operational flexibility. An integrated strategy results in a complex, time dependent planning problem that considers different investment alternatives. Figure 2.11 summarizes the requirements for an integrated planning strategy for meshed HV systems.

Figure 2.11: Goal of the planning strategy and resulting requirements.
2.4. Resulting Requirements for a Time-Series-Based Planning Strategy

Considerations

When planning the power system, the technical constraints must be satisfied in each analyzed loading situation. These constraints include voltage limits, loading limits of transformer and lines as well as security constraints in \( N-1 \) cases. Operational and conventional measures must be considered in planning to satisfy these constraints. On the operational side, power system operators can directly optimize tap-changer positions of transformers and the current switching state. Indirectly the operator can curtail generated energy generated by WPP, PV, or other RES. If storage systems are installed in a system, the change of charge- and discharging cycles can change the PFs in a system as well. These time dependent options must be considered when designing the grid. Reactive power compensation by RES can mitigate voltage problems and is another degree of freedom for the power system operator. Conventional measures are the replacement and installation of new lines or transformers in a grid. These investments are discrete and long term decisions in comparison to the use of operational flexibility.

Requirements

Different requirements result from considered technical constraints, operational flexibility, and conventional measures. All calculations require a power system model to evaluate the technical limits. When taking into account the SCP or \( N-1 \) security policy, a fast and automated analysis is needed. To model operational flexibility, time-series-based simulations are required so that control capabilities (flexibilities) of RES and storage systems are taken into account in planning. A generic storage system model can represent electric cars, stationary batteries, or power to gas systems. Different curtailment strategies of RES allow comparing their differences in resulting costs and simulation time. Direct control measures such as tap-changer and switches need to be implemented in the strategy as well. When regarding the conventional measures, different line standard types and transformers sizes allow minimizing costs and designing the system according to its needs. These requirements result in a time depended mixed-integer non-linear optimization problem. A trade-off between accuracy and computational effort must be found to be applicable in practice allowing to analyze multiple years or scenarios.
Evaluation

Results of the time series simulation are PFs and voltages for each time step of the regarded time horizon. When additionally considering the $N-1$ security policy, $N$ results for each time step are available. A fast data analysis is, therefore, necessary to evaluate the technical limits. On the economic side, different expenditures result from the optimization. These include the annuity of replaced or newly installed lines and transformers as CAPEX. With the discounted cash flow method, the annuities can be compared to the OPEX of the operational measures such as the curtailment of generation or the use of storage systems. In this thesis, it is assumed that the owner of RES and storage systems are separated entities. Therefore, installation costs of storage systems or reactive power compensation by capacitive or inductive loads are not considered as CAPEX. Adequate visualization of technical and economic results enables a power system planner to make a final investment decision while considering operational flexibility and conventional measures in the planning of meshed power systems.
3 Power System Analysis and Planning Methods

This chapter outlines relevant methods for power system analysis and planning. Time-series-based power system planning requires to simulate power systems with iterative PF analysis. Relevant power system analysis methods are described in Section 3.1. Time series simulations result in long simulation times, which can be reduced by applying ML methods. The concepts of ML, data preprocessing methods and different algorithms are explained in Section 3.2. Results from the time series analysis are loading situations which are the basis for the combinatorial optimization of the system. Section 3.3 outlines the different combinatorial optimization problems and solution methods. In Section 3.4, the chosen approach for the following implementation is summarized.

3.1 Power System Analysis

Power system analysis methods are applied in live operation and when planning the system. Common methods include PF studies, short circuit analysis calculations, and system state estimation. The most relevant analysis method for time series planning is the PF study, which is explained in Section 3.1.1. This and other methods are implemented in the open source tool pandapower. Section 3.1.2 details relevant details of pandapower.
3.1.1 Power Flow Study

PF studies are the basis of designing future power systems and are applied to determine the best operation of existing systems. The information provided by a PF study is the magnitude $|V_i|$ and phase angle $\delta_i$ of the complex voltage $V_i$ at each bus $i \in N$. With $V_i$ and the nodal admittance matrix $Y_{bus}$, the power flowing in each line and transformer can then be determined. Equations (3.1) and (3.2) constitute the polar form of the PF equations:

$$P_i = \sum_{j=1}^{N} |Y_{ij}V_iV_j|\cos(\theta_{ij} + \delta_j - \delta_i)$$ (3.1)

$$Q_i = -\sum_{j=1}^{N} |Y_{ij}V_iV_j|\sin(\theta_{ij} + \delta_j - \delta_i)$$ (3.2)

$P_i, Q_i$ denote the real and reactive power entering the network at bus $i$. $Y_{ij}$ is the entry of the complex $N \times N$ nodal admittance matrix $Y_{bus}$ in the $i$th row and $j$th column:

$$Y_{ij} = |Y_{ij}|\angle \theta_{ij} = |Y_{ij}|\cos \theta_{ij} + j|Y_{ij}|\sin \theta_{ij} = G_{ij} + jB_{ij}$$ (3.3)

$G_{ij}$ and $B_{ij}$ denote the real and imaginary part of $Y_{ij}$. The voltage at a bus $i$ is given in polar coordinates by:

$$V_i = |V_i|\angle \delta_i = |V_i|(\cos \delta_i + j \sin \delta_i)$$ (3.4)

In a PF study, the real power $P_D$ and reactive power $Q_D$ demand of load buses are known. These bus types are commonly referred to as PQ-buses. Smaller or static generators can be modeled as PQ-buses by applying negative values for $P_D$ and $Q_D$. The real power injection $P_g$ and the voltage magnitude $|V_g|$ are the known values of larger generation units with voltage regulators. These bus types are called PV-buses since $P_g$ and $|V_g|$ are constant values in the PF formulation. To be able to solve the system of equations defined by (3.1) and (3.2), one reference or slack bus must be defined. For this node, the known variables are the voltage magnitude $|V_r|$ and angle $\delta_r$. At the slack bus, the mismatch between power demand and generated power is balanced. Typically, the bus with the largest generator connected
or the connection to the upper voltage level is chosen as the slack bus [148]. Multiple slack buses can be modelled with the distributed slack method. This requires the definition of a participation factor for each slack, resulting in a more complex problem [149]. In a system with \( N \) buses of which \( G \) buses are generators (PV-buses), there are \( 2N \) quantities specified and \( 2N - G - 2 \) equations to be solved. The PF problem is non-linear. Hence, PF calculations employ iterative techniques such as the Newton-Raphson procedure. The Newton-Raphson method solves equations (3.1) and (3.2) until the mismatches \( \Delta P_i \) and \( \Delta Q_i \) are smaller than a specified tolerance [148].

### 3.1.2 pandapower

In research, PF studies are often conducted with state-of-the-art open-source tools such as MATPOWER, PyPower or pandapower [116, 150, 151]. Results from this thesis, an improved Newton-Raphson implementation, and the time series module, are integrated into pandapower. pandapower is an open-source network calculation program aimed to automate the analysis and optimization of power systems. It uses the data analysis library pandas [152] and is compatible with the commonly employed MATPOWER case format [150]. The pandapower library provides the most commonly used static network analysis features, including PF, OPF, short-circuit analysis, and state estimation. Its data structure contains common nameplate parameters for convenient parametrization of elements such as transformers or power lines. pandapower converts the element models to their electric equivalent representation to conduct power system analysis. Figure 3.1 shows the conversion process from the element-based data structure into a bus-branch model (BBM).

The data structure of the BBM model is similar to that of a pypower casefile with extensions include parameters like asymmetrical impedances or constant current load. A conversion from the element-based pandapower format to the BBM is difficult for several reasons. First, the BBM requires consecutive indices starting from zero, whereas the pandas indices can be unsorted. Second, elements such as the three-winding transformer are converted to multiple internal buses and branches requiring additional auxiliary buses. Third, the power injections of multiple static
loads, generators, or ward elements at one bus must be summarized to single PQ-elements. Fourth, the ideal switch model requires to fuse buses, create additional auxiliary buses, or to reconnect branches. Finally, pandapower identifies areas without a connection to a slack or generator bus to maintain connected components. After conducting the electrical analysis based on the BBM, results must be converted back from the internal data-structure to the element-based model [116]. This convenience comes with the drawback of higher calculation times. For time series analysis, however, the conversion time can be saved by keeping parts of the internal data structure in memory. This is explained in detail in Section 4.2.2.

Figure 3.1: Electric power system analysis in pandapower (taken from [116]).

### 3.2 Approximation Methods for Time Series Simulations

The fast calculation of PF results is needed to analyze multiple time series. A method to approximate PF calculations is to build ML models. ML models are computer programs, which learn from experience with respect to some class of tasks
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and performance measures. The model learns if its performance at these tasks improves with experience [153]. With increasing computational power, ML research has gained momentum in various fields [154]. In power systems, ML methods are used to predict PF results [155, 156] or to estimate system states [157]. A general overview of recent studies in the context of planning and operation with artificial intelligence is given in [158]. In this thesis, regression and classification ML methods are implemented to identify critical loading situations in a time series simulation. Section 3.2.1 explains the difference between ML regression and classification. Relevant data preprocessing concepts are detailed in Section 3.2.2. The applied ML algorithms in this thesis are outlined in Section 3.2.3.

3.2.1 Regression and Classification

Figure 3.2 shows an example of the prediction of PF results. A regression model directly predicts certain PF results, e.g., the line loading or bus voltage magnitudes as shown in Fig. 3.2 (a). Only a fraction of the AC PF results are calculated for training. The regressor then predicts the remaining values. A classifier predicts whether a time step is critical or not as shown in Fig. 3.2 (b).

![Figure 3.2: Prediction targets of regression and classification methods within time series simulations.](image)

The algorithms applied in this thesis belong to the category of supervised learning. By observing several examples of an input vector $x$ and an associated output
value or vector $y$, the algorithm learns to predict $y$ from $x$ by estimating a function $y = f(x)$. The term supervised learning originates from an imaginary teacher who shows the machine learning system if its prediction during training was right or wrong. In unsupervised learning, no such teacher exists. The algorithm must learn to make sense of the data on its own [154].

**Regression**

Regression analysis is the process of estimating the relationships between dependent variables or *output* variables and one or more independent variables, also called *features*. The regression problem is solved by a regression learning algorithm, which takes a collection of labelled examples to produce a model. The trained model is then able to predict continuous output variables from unknown features [159]. The target of the regression learning algorithm is to estimate the function $f(x_i)$ that most closely fits the data. Most regression models assume that $y_i = f(x_i) + e_i$ with $e_i$ representing an additive error resulting from random statistical noise or un-modeled determinants of $y_i$ [160]. The model is trained with a collection of labelled examples $\{(x_i, y_i)\}_{i=1}^{C}$, where $C$ is the size of the collection, $x_i$ is the $D$-dimensional feature vector of example $i = 1, ..., C$, $y_i$ is a real-valued target and every feature $x_i^{(j)}$, $j = 1, ..., D$, is a real number. A simple regression algorithm is *linear regression* that models a linear combination of the input features $x_i$:

$$f_{\text{linear}}(x) = w \cdot x + b \quad (3.5)$$

In (3.5), $w$ is a $D$-dimensional vector of parameters and $b$ is a real number [159]. Figure 3.3 shows linear and non-linear regression examples. In this thesis, regression models are applied to approximate the PF equation, which consists of trigonometric functions and is non-linear. Therefore, sophisticated regression algorithms, such as artificial neural networks (ANNs), are needed to estimate the non-linear function.

Common regression metrics are the mean and max. absolute error. The mean absolute error is defined by equation (3.6):
mean absolute error = \frac{1}{n_{\text{samples}}} \cdot \sum_{i=0}^{n_{\text{samples}}-1} |y_i - \hat{y}_i| \quad (3.6)

with \( y \) the true output vector, \( \hat{y} \) the predicted vector and \( n_{\text{samples}} \) the number of samples in the dataset. Similarly, the max. absolute error is defined by (3.7):

max. absolute error = max(|y - \hat{y}|) \quad (3.7)

**Classification**

Classification is the task of assigning a discrete label to an unlabeled input example. Compared to the regression problem, a label belongs to a finite set of classes in a classification problem. A well-known example is spam detection, which falls into the category of binary classification. If more than two classes are to be predicted, the classification problem is called multiclass classification. A classification learning algorithm solves the classification problem. It takes a collection of labeled examples as inputs for training and produces a model for the labelling of unlabeled data. This model either directly outputs a label or a number, e.g., a probability that can be used to deduce the label [159].

In this thesis, binary classifiers distinguish between critical and uncritical time steps. The classifier should preferably predict uncritical time steps as critical (false negatives) and be less precise than fail to notice critical time steps. Different metrics are commonly applied to assess the performance of classifiers. Recall (3.8) measures the fraction of true positive (TP) classifications over the total amount of relevant instances. The relevant instances are the sum of TP and false negative (FN) classifications. In this thesis, TP values are the correctly identified critical
time steps, and FN values are critical time steps which have been mislabelled as uncritical:

\[
\text{recall} = \frac{TP}{TP + FN}
\]  

(3.8)

It is of high importance to identify all critical loading situations. Thus, FN classifications should be minimized and recall maximized. Some uncritical time steps are rather tolerated to be identified as critical (false positive (FP)) than a lower recall score. The precision score measures this ratio of misclassification:

\[
\text{precision} = \frac{TP}{TP + FP}.
\]

(3.9)

When classifying critical loading situations, maximizing recall is more important than maximizing precision. The accuracy score (3.10) measures the ratio of correct classifications to all classifications. Correctly identified uncritical time steps are true negative (TN) values. The accuracy metric is less suitable for imbalanced datasets, where the majority of time steps are uncritical, and only a fraction is critical. In this case, the accuracy score is high by default when labelling every time step as uncritical.

\[
\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}.
\]

(3.10)

### 3.2.2 Data Preprocessing

Data preprocessing is a step to prepare the available data for training and prediction. Different preprocessing methods are explained in this section, including oversampling of imbalanced datasets, cross validation, and feature selection.

#### Imbalanced Datasets

A classification data set is imbalanced when one class is underrepresented as shown in Fig. 3.4 for binary classification. In time series calculations, the data set is often imbalanced since the majority of time steps is *uncritical* with a few critical time steps to be identified (compare Fig. 3.2). The accuracy would be very high if all of the time steps are labelled as *uncritical* by default. However, recall is small in this case since the number of FN values is maximal.
Two methods are applied in this thesis to solve this issue: the prediction of probabilities to which class the time step belongs and oversampling of the dataset. Instead of directly predicting the class, (binary) classifiers are able to predict a probability matrix of the dimension \((T, 2)\). The first index refers to the probability of a time step \(t \in T\) being \textit{uncritical}. The second index refers to the probability that the time step is \textit{critical}. By reducing the probability threshold for the \textit{critical} class, the number of positive predictions and recall increase while precision decreases. Oversampling raises the importance of one class by increasing the number of examples of this class with artificial copies. Popular methods are synthetic minority oversampling technique (SMOTE) [161] and adaptive synthetic sampling (ADASYN) [162], which work similarly. For a given example \(x_i\) of the minority class, a set \(S_k\) is picked that consists of \(k\) nearest neighbours of this example. Then, a synthetic example \(x_s\) is created as \(x_i + \lambda(x_{zi} - x_i)\), where \(x_{zi}\) is an example of the minority class chosen randomly from \(S_k\). The interpolation hyperparameter \(\lambda\) is a random number in the range \([0, 1]\) [159].

**Cross Validation**

Cross validation (CV) is a model validation technique for assessing how the trained prediction model will generalize to an independent data set. The goal of CV is to reduce problems like overfitting or a selection bias by giving insight on how the model will generalize to an independent and unknown dataset. It is mainly applied to estimate how accurately a predictive model will perform in practice. In CV, the model is given a dataset of known data on which training is run (training dataset), and a dataset of unknown data (test dataset) against which the model is tested. CV is performed by iteratively training the model in multiple CV iterations. In each iteration, the data set is divided into a different test- and training sets. Figure 3.5
shows three exemplary cross validation methods: k-fold, shuffle and time series splitting. A k-fold validation splits the data sample into k coherent training and test sets. A shuffle split is dividing the data randomly. With a time series split, the data is also divided into coherent parts, but only parts of the data sample are used for testing [163, 164].

**Figure 3.5:** Exemplary data sample (a) and cross validation methods (b)-(d). The exemplary data sample shows the first k-fold iteration split.

### Hyperparameter Optimization

Hyperparameters are properties of ML algorithms that influence how well the algorithm learns. Examples are the number of layers of an ANN, their amount of neurons or the learning rate. Hyperparameters are not learned from data but must be set by the data analyst before the learning process [159]. The choice of suitable hyperparameters for a given learning task depends on experience. However, automated optimization tools exist which either randomly choose hyperparameters or use genetic programming methods for the optimization [164, 165].

### Feature Selection and Dimensionality Reduction

Feature selection and dimensionality reduction seek to reduce the number of attributes in a dataset. Feature selection is the process of selecting a subset of relevant features for use in model creation. This differs from dimensionality reduction in the way that dimensionality reduction creates new combinations of features,
whereas feature selection methods only select attributes present in the data without changing them. Examples for feature selection are univariate selection or feature selection by using other models, e.g., tree-based feature selection. Univariate feature selection works by selecting the best features based on univariate statistical tests. Feature selection based on tree estimators selects the most important features, identified by the tree-model, as inputs for another model. An example of a dimensionality reduction method is the Principal Component Analysis (PCA), as shown in Fig. 3.6. The input data in Fig. 3.6 (a) is narrowly distributed and has the dimension $D_{in} = 2$. The PCA defines a new coordinate system with axis according to the highest variance of the data. In Fig. 3.6 (b) the two new axis are shown as vectors. Their length reflects the variance in this direction. The largest principal components are selected to reduce the dimensionality of the original data set, and the data is projected on them. This is shown in Fig. 3.6 (c) by the orange data points, which have the dimension $D_{PCA} = 1$ [159].

\[ \text{Figure 3.6: PCA example – (a) original data; (b) two principal components displayed as vector; (c) the data projected on the first principal component (taken from [159])}. \]

### 3.2.3 Machine Learning Algorithms

A multitude of ML methods are currently in development. Two common algorithms are explained in this section. These methods support multi output regression/classification as needed for time series predictions.
### Tree Learning

A Decision Tree (DT) is an acyclic graph that is applied to make decisions. The tree examines a specific feature $j$ of the input vector in each branching node of the graph. If the value of $j$ is below a specific threshold, it follows the left branch. Otherwise, the right branch is followed. When the tree reaches its leaf node, it decides to which class the example belongs. Random Forest (RF) and Extremely Randomized Trees (ETs) belong to the category of tree learning methods. These construct a multitude of DTs during training and decide by a majority voting the final category (see Fig. 3.7). Gradient boosting produces a prediction model in the form of an ensemble of weak prediction models. These weak prediction models are typically DTs [159].

![Figure 3.7: RF, ET, and gradient boosting concept. Multiple DTs are applied to predict the category of class by majority voting.](image)

### Artificial neural networks

An ANN is described by a mathematical function of the form:

$$y = f_{\text{NN}}(x)$$  \hfill (3.11)

The function $f_{\text{NN}}$ is a nested function consisting of one or multiple functions or layers. If the ANN consists of more than one layer it is a deep neural network:

$$y = f_{\text{NN}}(x) = f_L(f_{L-1}(\ldots(f_2(f_1(x))))))$$  \hfill (3.12)

A common type of neural networks are feed-forward neural networks. In this thesis, the feed-forward multilayer perceptron (MLP) architecture is applied, as shown in Fig. 3.8.
A property of feed-forward networks is that inputs to one layer are outputs of the previous layer. The inner functions \( f_i, i \in [1, L - 1] \) are vector functions of the following form:

\[
    f_i(z) = g_l(W_l \cdot z + b_l)
\]  

(3.13)

with \( l \in [1, L] \) the layer index. The function of the last layer \( f_L \) is either a scalar function or a vector function depending on the problem. The function \( g_l \) is an activation function, which is chosen prior to the training process. Typically, it is a non-linear function which normalizes its input. Common used activation functions are the sigmoid function or the hyperbolic tangent. During the learning process the weight matrices \( W_l \) and bias vector \( b_l \) are adjusted by gradient descent by optimizing a particular cost function, e.g., the mean squared error [159]. One of the most popular adaptive learning rate optimization algorithm, designed specifically for training deep neural networks, is adaptive moment estimation (ADAM) [166].

### 3.3 Optimization in Power System Planning

Results from the time series analysis are the basis for power system optimization. Different measures are to be considered during the optimization, including the installation or replacement of lines and transformers, changing the switching state,
or the control of operational flexibility. By considering these measures, a combinatorial optimization problem results. Constraints include compliance with technical restrictions such as bus voltage limits and thermal loading limits of power lines and transformers. AC PF constraints are to be regarded in the optimization to comply with these limits. Since the AC PF formulation is non-linear, the problem is non-convex. Figure 3.9 illustrates the non-convex solution space and shows multiple local optima, which are feasible points with objective values that are inferior to the global optimum [77]. It is the objective of the optimization method to find this global optimum. However, for most problems, multiple solutions exist, of which many may be local solutions [32].

![Solution Space](image)

**Figure 3.9:** Conceptual illustration of the solution space with local optima and the global optimum (adapted from [77]).

Section 3.3.1 details a OPF formulation applied to solve the economic dispatch problem. This formulation is the basis for most combinatorial optimization problem formulations. Section 3.3.2 explains the concept of combinatorial optimization and outlines two solution strategies: heuristic optimization and mathematical programming methods.

### 3.3.1 Optimal Power Flow

Power system operators want to reduce costs resulting from losses of power transmission. These costs are minimized by determining the optimal output of electricity generation facilities to meet the system load. This optimization is referred to as the economic dispatch (ED) problem. ED is the calculation that finds the lowest-cost generation dispatch for a set of generators that are constrained by their generation
limits. The result is a generation set-point that equals the total load plus losses. In this optimization, the limited transmission capacity is not considered. This is solved by the OPF formulation. The OPF formulation forms the basis for many applications. It minimizes a specified cost function subject to the PF equations and engineering limits. The OPF couples the ED calculation with the PF constraints so that the ED and the PF problem are solved simultaneously. The ED is constrained to meet transmission system limits such as real and reactive PF limits on lines or transformers and voltage limits on buses. The result is the generation dispatch representing the minimum cost per hour generation, which complies with the PF limits at that optimum [167]. The optimization problem can be formulated as follows:

\[
\text{minimize: } \sum_{k \in G} f_k(P_{g,k}) \tag{3.14}
\]

subject to:

\[
(S_{g,i} - S_{D,i}) = V_i \left( \sum_{j=1}^{N} Y_{ij} V_j \right)^* \quad \text{- coverage of system load} \tag{3.15}
\]

\[
S_{g,k}^{\min} \leq S_{g,k} \leq S_{g,k}^{\max}, \forall k \in G \quad \text{- generator limits} \tag{3.16}
\]

\[
\angle V_r = 0 \quad \forall r \in R \quad \text{- reference bus angle limits} \tag{3.17}
\]

\[
v_i^{\min} \leq |V_i| \leq v_i^{\max}, \forall i \in N \quad \text{- voltage magnitude limits} \tag{3.18}
\]

\[
\theta_{ij}^{\Delta i} \leq \angle (V_i V_j^*) \leq \theta_{ij}^{\Delta u}, \forall (i, j) \in B \quad \text{- voltage angle difference} \tag{3.19}
\]

\[
|S_{ij}| \leq s_{ij}^{u}, \forall (i, j) \in B \quad \text{- branch thermal limits} \tag{3.20}
\]

\[
|I_{ij}| \leq i_{ij}^{u}, \forall (i, j) \in B \quad \text{- branch current limits} \tag{3.21}
\]

with:

- \( B \) - set of branches
- \( G \) - set of generators
- \( N \) - set of buses
- \( R \) - set of reference buses
- \( S_{g,k} \forall k \in G \) - generator complex power dispatch
- \( V_i \forall i \in N \) - bus complex voltage
3.3. Optimization in Power System Planning

\[ S_{ij} \quad \forall (i,j) \in B \] - branch complex PF

\[ S_{g,k}^{\text{min}}, S_{g,k}^{\text{max}} \quad \forall k \in G \] - generator complex power bounds

\[ S_{D,i} \quad \forall i \in N \] - load complex power consumption

\[ v_i^{\text{min}}, v_i^{\text{max}} \quad \forall i \in N \] - voltage bounds

\[ s_{ij}^{\text{u}} \quad \forall (i,j) \in B \] - branch apparent power limit

\[ i_{ij}^{\text{u}} \quad \forall (i,j) \in B \] - branch current limit

\[ \theta_{ij}^{\Delta l}, \theta_{ij}^{\Delta u} \quad \forall (i,j) \in B \] - branch voltage angle difference bounds

The objective function (3.14) minimizes the generation costs for each generator. Constraints include the coverage of the system load by these generators (3.15) and multiple limit definitions (3.16)-(3.21) for generators, bus voltages and branch flows. This set of equations is only one example of an OPF formulation.

3.3.2 Combinatorial Optimization

Power system planning requires to consider binary decision measures in the optimization of the power system in addition to the continuous generation variables. A measure is defined as a single action that can be applied to the grid model to change one property of the grid. A solution is obtained by choosing a combination of possible binary measures from a pre-defined set. Incorporating binary measures in the problem formulation results in a combinatorial optimization problem. Every set of measures is codified as a binary set \( M = m_0, ..., m_N \) where \( m_i = 1 \) corresponds to an applied measure and \( m_i = 0 \) means that the measure is not applied. In this thesis, three types of binary measures are considered during an optimization:

- switching measures – opening/closing of switches,
- replacement measures – replacement of existing power lines or transformers,
- additional line measures – installation of additional lines between two substations.
Figure 3.10 shows an example of these measure types. $|M|$ defines the cardinality, which is the number of binary optimization variables of the measure set. The cardinality is $|M| = N_B$ if all branches (lines and transformers) can be replaced. It is $|M| = N_{sw}$ if switching measures are considered, with $N_{sw}$ being the switch measures. If only additional lines are in the measure set, the cardinality is $|M| = N_{al}$, with $N_{al}$ the available additional power lines. In a combined optimization the cardinality is $|M| = N_B + N_{sw} + N_{al}$. It is the optimization goal to find a subset of these $2^{|M|}$ measures that satisfy the PF constraints.

![Figure 3.10: Combinatorial optimization measure types: (a) switches, (b) line or transformer replacements, (c) installation of additional lines, d) a combination of all measures. $|M|$ is the cardinality of the measure set $M$ and defines the number of optimization variables.](image)

When incorporating binary decision measures in the OPF formulation, the optimization problem is a MINLP. This problem type is classified as NP-hard and cannot be solved in polynomial time [31]. A combined optimization problem considers all available measures, including line-switches of all existing lines, line replacements, and additional lines. The objective function (3.14) is extended to (3.22) minimizing the total cost of newly installed $c_{al}$ and replaced branches $c_{b}$, for switching operations $c_{sw}$, and real power generation:

$$\text{minimize:} \quad \sum_{k \in G} f_k(P_{g,k}) + \sum_{b \in N_B} c_b + \sum_{al \in N_{al}} c_{al} + \sum_{sw \in N_{sw}} c_{sw} \quad (3.22)$$
Two approaches are common to solve combinatorial optimization problems: meta-heuristic optimization methods and mathematical programming. These methods are explained in the following section.

**Metaheuristic Optimization**

Metaheuristic methods are generally easier to implement than mathematical programming models since no formulation of the optimization problem is required. Instead, the solution space is iteratively searched by systematically evaluating different measure combinations. Heuristic optimization methods are proven to be robust and able to find near-optimal solutions for complex, large-scale planning problems [30]. However, it is never guaranteed that these methods find the global optimum for realistic grid sizes. A general heuristic optimization process is depicted in Fig. 3.11:

![Figure 3.11: General metaheuristic optimization method.](image)

The optimization starts with an initial solution $s$, which can be an empty set or otherwise generated from the input measures $M$. The current best solution $s^*$ is assigned the highest cost value $c_{s^*} = \infty$. After applying the solution to the current grid state (net), the metaheuristic evaluates the PF constraints. The current solution $s$ becomes the current best solution if the costs of the current solution $c_s$ are lower than the cost of the current best solution. Otherwise, the metaheuristic modifies the current solution according to its strategy. This process is iterated until
no evaluations are left or a pre-defined time limit is reached. Exemplary heuristic optimization algorithms are:

**Hill Climbing (HC):** HC is a simple stochastic local search algorithm. Based on an initial candidate, it iteratively moves to a random neighbouring candidate $s_0$, if this candidate decreases the cost function. This procedure is repeated until no improving step is available in the neighbourhood. An advantage is that HC can find a solution without violated restrictions within a few iterations. However, the HC may end up in a local optimum quickly. Restarting the algorithm several times is a simple approach to obtain better solutions. A restart, however, leads to a loss of all information collected in the search process so far. HC is classified as a greedy algorithm and has a high exploitation characteristic [48].

**Iterated Local Search (ILS):** ILS moves through the solution space, starting at a local optimum, to neighbouring (improved) local optima. It escapes local optima by slightly perturbing the current solution. ILS searches for better solutions in a reduced solution space defined by an arbitrary black-box heuristic. In this thesis, the HC algorithm is used as the black-box heuristic for the ILS [48, 168].

**Genetic Algorithm (GA):** A GA applies different bio-inspired operators to solve an optimization problem. Individual candidates change their properties, also called genes, through evolution and selection. Standard evolutionary operators are mutation, the change of one or more properties of a candidate, and crossover, which is an exchange of a certain number of genes between two candidates. These operators are applied with a certain probability so that some individuals go through to the selection unchanged. Numerous different selection mechanisms exist. A common strategy is to use the tournament method to select the individuals of the next generation, in which $N$ randomly selected individuals are compared, and the one with the lowest cost value is transferred into the next generation. In the first generation, a number of (random) individuals must be generated. During multiple generations, neighbouring candidates are found through mutation, while the entire search space is considered with crossover [169].
Grey Wolf Optimizer (GWO): GWO is a metaheuristic algorithm, inspired by the hierarchy and hunting mechanisms in a pack of grey wolves. Different types of wolves exist, often referred to as $\alpha$, $\beta$, $\delta$, and $\omega$ wolves, which simulate a leadership hierarchy from the top ($\alpha$) to bottom ($\omega$). The prey is *hunted* by searching it, encircling and attacking it. The social hierarchy is determined by using the cost values of the current solution. The solution with the lowest cost is the $\alpha$ wolf, while the second-best is the $\beta$, the third-best is the $\delta$, and all other wolves are $\omega$ wolves. The search is performed by encircling the best solution starting from (randomly) initialized candidates. This is implemented by defining a circle-shaped neighbourhood around the evaluated solutions, in which new candidates are created. The position of the prey is in between the $\alpha$, $\beta$, and $\delta$ solutions. Attacking is a move of the wolves into the direction of the prey. The radius of the neighbourhood in the encircling mechanism decreases with more iterations [170].

Fireworks Algorithm (FWA): FWA is a swarm intelligence algorithm, based on the dynamics of a fireworks explosion. Two explosion processes are performed, which implement the search function for the optimizer. First, a set of $N$ starting locations are selected as the basis for fireworks. Sparks are then set off in the immediate neighbourhood around these locations. The number of generated sparks and their amplitude, which is the distance from the original fireworks position, are formulated by equations. Two ways exist for generating sparks. One is based on uniform distribution, and the other is based on the Gaussian distribution. The dimension, in which the original fireworks position and the spark’s position are altered, is chosen randomly. The new fireworks positions and sparks for the following iteration are selected from the existing fireworks with a certain probability of $p_a$. The best candidate is always transferred to the next iteration. The probability $p_a \in [0, 1]$ with $p_a \in IR$ is proportional to its distance to other candidates. It is the intention to obtain locations with a high distance to each other in order to avoid limiting the exploration of the algorithm [171].
**Mathematical Programming**

While metaheuristics repeatedly solve steady-state AC PF problems, mathematical programming methods work differently. The PF equations are boundary conditions to an optimization problem that minimizes a specific optimization goal. A solver tries to find a valid assignment of the optimization variables to minimize costs for generation, losses, or grid-extension. Mathematical optimization or mathematical programming is a branch of operations research [172]. It is concerned with methods for solving problems on finding the extrema of functions on sets defined by linear and non-linear constraints in a finite-dimensional vector space. Constraints may include equalities and inequalities [173].

For realistic grid sizes, the state-of-the-art solvers are often not able to determine solutions for the MINLP AC PF formulation. A solution strategy is to approximate or relax boundaries to obtain a convex solution space. By simplifying the problem, solutions can be obtained in linear or polynomial time. The drawback of this approach is that the determined solution is either not optimal or not AC feasible. Infeasibility means that when running an AC PF calculation with the obtained switching state or line installation, voltage or line loading limits are still violated. Common simplifications include the linear DC approximation or quadratic SOC relaxations. Figure 3.12 illustrates the difference between a convex relaxation and a convex approximation. The convex relaxation wraps the non-convex solution space and includes the global optimum solution. In comparison, the approximation does not necessarily include the global optimum since it only covers parts of the solution space [77].

![Convex Relaxation and Approximation](image-url)

**Figure 3.12:** Schematic representation of convex relaxation and an approximation for the non-convex solution space (adapted from [77]). A relaxation always includes the optimum; the approximation must not include it.
3.3. Optimization in Power System Planning

A common linear approximation is the DC PF formulation. The non-linear AC system is simplified to a linear form by assuming that:

- line conductances $G_{ij}$ are small in comparison to the line susceptances $B_{ij}$ so that $G_{ij} \sin(\delta_i - \delta_j) \ll B_{ij} \cos(\delta_i - \delta_j)$,

- voltage angle differences are small so that $\sin(\delta_i - \delta_j) \approx (\delta_i - \delta_j)$ and $\cos(\delta_i - \delta_j) \approx 1$,

- and bus voltage magnitudes are flat ($|V_i| = 1.0 \text{ p.u.} \forall i \in N$).

Based on these assumptions, the only unknown variables of the PF equations are bus voltage angles. Therefore, the reactive power injection equation (3.2) is zero ($Q_i = 0$) and the real power injection equation (3.1) is converted to:

$$P_i = \sum_{j=1}^{N} B_{ij} (\delta_j - \delta_i)$$  (3.23)

As a result, the PF through a branch $ij$ is linear function of the bus voltage angles and the branch reactance $X_{ij}$ [174]:

$$P_{B,ij} = \frac{1}{X_{B,ij}} (\delta_j - \delta_i)$$  (3.24)

A well-known open-source mathematical optimization framework is PowerModels.jl [54]. PowerModels.jl is a package written in the julia programming language [175] and based on JuMP [176] for steady-state power network optimization. It allows parsing and modifying network data, and is designed to enable computational evaluation of emerging power network formulations and algorithms in a common platform. PowerModels.jl decouples the problem formulation in two parts: First, the problem specifications to solve, e.g., PF and OPF problems; Second, the network formulations (e.g., AC, DC-approximation, SOC-relaxation). With this approach, PowerModels.jl defines a wide variety of power network formulations, which then can be compared on common problem specifications [54]. In this thesis, PowerModels.jl is called via pandapower-interface, which as a wrapper to the PowerModels.jl optimization in julia. The interface is developed as part of this thesis and was first published in pandapower version 2.0 [115].
3.4 Choice of Procedure

Two tasks are essential when implementing a time-series-based power system planning strategy. First, rapid identification of critical load cases from time series simulations is needed. Second, the minimization of total expenditures (TOTEX) in grid planning based on the simulation is required. Advantages and drawbacks of the methods to accomplish these tasks are compared in Fig. 3.13. Based on this comparison, the research need is identified and outlined in this section.

**Task 1: Rapid identification of critical load cases from time series simulations**

- **Full Power Flow**
  - Correct result
  - Longer simulation time
  - Time savings with tailored implementations only

- **ML Approximation**
  - Fast calculation
  - Approximation error
  - Training data needed

**Research Need**
- Reduction of simulation time and conversion overhead
- Identification of the best approximation method
- Selection of training data

**Task 2: Minimization of TOTEX for grid planning**

- **Metaheuristic Optimization**
  - Easier to implement
  - Large scale problems solvable
  - No guarantee of optimality
  - Multifold of methods exist

- **Mathematical Programming**
  - AC-solution is optimal
  - AC problem hard to solve for power grids of realistic size
  - Relaxation/approximation solutions are not optimal

**Research Need**
- Identification of suitable metaheuristic and mathematical programming methods
- A multi-year planning strategy to find investment decisions considering CAPEX and OPEX

**Figure 3.13:** Tasks, methods and research need in time-series-based planning.

**Task 1: Rapid identification of critical load cases from time series simulations**

Time series simulations are required to integrate operational flexibility in the planning of HV power systems. Operational models of RES, storage systems, switchgear, and other equipment are to be implemented to perform time series simulations. These simulations require longer simulation times than to conventional power system planning methods. The simulation time is often too long for practical analysis,
and a reduction is needed when calculating quasi-static AC PF results. Therefore, a trade-off between simulation time and model detail must be found. Time savings are either possible by implementing tailored simulation models for time series analysis or by applying approximation methods. The advantage of a tailored AC PF implementation is that there are no errors in comparison to the ML approximations. The ML methods, however, allow reducing the calculation time further. For ML training, suitable training data is needed to generate appropriate prediction models. The question arises on how to select and pre-processes this data to reduce the approximation error. Additionally, the different ML methods must be compared to identify the method with the lowest prediction error. In this thesis, several ML concepts are evaluated and tested to identify the most suitable method for PF predictions. The research need regarding time series simulations contains these questions:

- How to implement different control strategies with sufficient modelling detail without a significant increase in simulation time? Different models are to be implemented to simulate curtailment strategies, storage systems, and conventional measures such as tap-changer or power line switches.

- Which ML architecture is suitable for power flow approximations? Several architectures, including ANNs and DTs as well as regression and classification models, must be compared. Evaluation criteria are approximation error, training and prediction time.

- How to select and pre-process suitable data for training? The amount of necessary data for a low prediction error is to be identified, and sampling strategies are to be tested.

**Task 2: Minimization of TOTEX for grid planning**

The optimization of the power system requires to consider continuous and binary decision variables. This requirement results in a MINLP problem formulation. To solve such problems and to find an investment decision in the infrastructure, metaheuristic and mathematical programming methods can be applied. Metaheuristic methods have the advantage of being easier to implement and scale well on realistically sized problems. A disadvantage of metaheuristics is that there is no
guarantee of solution quality. Additionally, a multitude of methods exists which are more or less suitable for the planning problem. In comparison to the metaheuristics, mathematical programming methods require to formulate the planning problem. Mathematical models guarantee optimality when using the AC formulations of the problem. However, this formulation cannot be solved for realistically sized grids. Therefore, relaxation and approximation methods are in development, which simplifies the problem but cannot guarantee optimality. It is to be identified which method is appropriate for the time-series-based planning of meshed high voltage systems. A comparison of both methods is needed. Based on this comparison, a hybrid approach can be developed to use the advantages of metaheuristic and mathematical programming methods. Furthermore, the question arises on how to compare long-term investments in the infrastructure and the resulting CAPEX with OPEX for operational flexibility measures. Such a comparison requires a multiyear planning strategy, which helps power system operators to find an optimal investment decision. In the context of grid optimization, the following research questions arise:

- How to formulate the multi-year planning problem, including time series simulations? A problem formulation must be found, which is applicable to real power systems and results must be shown for realistic power system models.

- Which optimization strategies are suitable for power system planning? Are metaheuristics or mathematical programming methods able to solve the MINLP planning problem? Several metaheuristics, including greedy heuristics and evolutionary algorithms, as well as different mathematical formulations are to be compared.

- Is it possible to find a hybrid optimization strategy combining the advantages of both methods? An improved method is to be identified derived from the comparison of optimization strategies.
3.4. Choice of Procedure
4 Implementation of the Time-Series-Based Grid Planning Strategy

This chapter details the implementation of the time-series-based planning strategy. Section 4.1 shows an overview of the method. Section 4.2 introduces the time series module, integrated into the open source tool pandapower, and several methods to reduce the calculation time of time series analysis. Results of the analysis are the basis for the following optimization. Section 4.3 formulates the optimization problem and introduces a hybrid method that combines the advantages of heuristic and mathematical programming approaches in a multi-year planning strategy for meshed HV power systems.

4.1 Method Overview

Figure 4.1 shows an overview of the planning strategy.

**Input Data:** The grid input data must be provided in the pandapower format, which includes the current grid topology, switches, line and transformer data as well as loads and generators. Historical or synthetic time series for load and generation are additional required inputs. Future demand and generation increase is considered by defining growth factors per year or by providing additional time series for the planning horizon. The definition of planning premises includes the discrete replacement or additional branch measures, the costs per km, and security constraints such as line loading limits and voltage boundaries. Operational measures include the curtailment of generation,
storage systems, switching measures and tap-changers. Further operational measures can be considered with the pandapower control module.

**Figure 4.1:** Methodical overview of the implemented time-series-based planning strategy. Contributions of this chapter are the time series simulation methods detailed in Section 4.2 and the optimization of flexibility and grid planning measures explained in Section 4.3.

**Time Series Simulation:** Section 4.2 details the time series simulation method. The time series simulation module, explained in Section 4.2.1, determines the thermal asset loadings occurring during the planning horizon for each line and transformer and bus voltages. During the simulation, operational schedules of available storage systems are determined. Contingency analysis is performed in each time step to consider $N$-1 security constraints. The SCP analysis simulates outages of lines and transformers. This process requires millions of PF calculations. Concepts to reduce the long calculation time are developed in Section 4.2.2 and Section 4.2.3. These methods including a
custom Newton-Raphson implementation and a ML method to rapidly predict bus voltage magnitudes and line loadings.

**Optimization:** Section 4.3 defines the planning problem and implements the power system optimization methods. A multi-year optimization strategy is developed in Section 4.3.1. Results of the time series simulation are critical loading situations or load cases. The load cases are derived from the time steps with the highest loadings and highest/lowest bus voltage magnitudes occurring during the simulated time frame. The load cases are the basis for the optimization, which determines the required measures to comply with the planning constraints. These measures include conventional grid planning measures and available operational flexibility. Section 4.3.2 outlines the operational optimization models including curtailment strategies and storage systems. Section 4.3.3 introduces the hybrid optimization method to solve the combinatorial optimization problem.

**Evaluation:** Results of the time series simulation and the optimization process are planning measures, operational flexibility control, and relevant technical and economic data. Planning results include the replaced and additional power lines and transformers per year. Operational measures include the curtailed energy, storage system schedules, tap-changer positions, reactive power compensation or an optimized switching state. Technical results are thermal loadings of power lines and transformers, bus voltages, and critical outages. Economic results include the OPEX and CAPEX per year.
4.2 Time Series Simulation

Time series calculations allow a more detailed simulation of power systems compared to conventional worst case methods. Consumption and generation are simulated in a quasi-static time domain to consider operational flexibility in the planning process. A major drawback of time series simulations are long simulation times. Section 4.2.1 introduces the time series module of pandapower and three methods are developed which reduce the calculation time of time series analysis. The first two methods are outlined in Section 4.2.2. The third method, a ML based approximation method, is detailed in Section 4.2.3.

4.2.1 Time Series Simulation Module of pandapower

Definition of Input Data

Power system planning requires to simulate future scenarios and to make assumptions on the increase of (renewable) generation, load growth, and the available storage capacity. Based on these assumptions, time series must be generated to simulate the possible future grid states and loading situations. The focus of this thesis is on the calculation and optimization methods based on previously measured or generated time series. At the HV level, measured time series at the HV side of 110 kV substations are usually available. Commonly, the real- and reactive-power values, as well as the voltage magnitude, are measured in 15 min time steps. In this thesis, these measurements are used as the input data for future calculations. Linear growth factors for load, generation, and storage flexibility are assumed and can be defined as inputs to the simulation strategy. Calculations are performed based on these scaled time series. Alternatively, time series can be generated with adequate simulation models or obtained for a specific region from open-data sources such as [144, 177, 178].
Time Series Module

With \texttt{pandapower} version 2.2, two additional modules were released in the open-source project: The \textit{control} and the \textit{time series} module [115]. The time series module, and some controllers of the control module (see Section 4.3.2), are developed as part of this thesis. The time series module executes time series simulations for a given grid model and time series data. The control module models the behaviour of different elements during a time series simulation. These elements include transformer tap changer, distributed energy resources (DERs) with Q-optimization and curtailment, or storage systems. Figure 4.2 shows the flowchart of the time series simulation module implemented in \texttt{pandapower}. Required input data are the grid model and time series data for loads, generators, and voltage measurements at slack-buses. Optionally, controllers can be defined, which may require additional inputs, e.g., a tap changer with pre-defined voltage set-points. At the beginning of each time step $t$, the complex power values $S$ of $PQ$-elements and voltage set-points of $PV$- or slack-elements are updated. During a time step, one or multiple PF calculations are performed depending on the convergence of the controller. A controller is converged when its set-point is reached. For example, the tap changer position is changed iteratively by a \textit{control step} until the desired voltage magnitude at the HV or LV bus is reached. It is possible to limit the number of iterations. If the desired set-point cannot be reached within the limit, the loop is aborted, and no result for the time step is available. After a control loop, the next time step $t = t + 1$ is calculated until not time steps are left.

![Flowchart of time series and control loop](image)

\textbf{Figure 4.2:} Time series and control loop as implemented in \texttt{pandapower} version 2.2 [115].
Identification of Relevant Load Cases

Time series simulations allow the analysis of periods, e.g., one or multiple years, to identify measures for grid planning. Results of time series simulations are mean or maximum asset loadings, which provide relevant information for asset managers and grid planners. Load cases are the relevant simulation results for grid planning. Load cases are grid states describing loading situations, with either line loading or bus voltage violations. Load cases are typically defined by assuming simultaneity factors in worst case based planning approaches. In time-series-based planning approaches, load cases are derived from the time series simulation. This concept is visualized in Fig. 4.3, which shows critical and uncritical time steps. Between time steps 54 – 92, the line loading limit is exceeded. A load case is created by storing the grid model in its current state for each of these critical time steps.

![Figure 4.3](image.png)

**Figure 4.3:** Exemplary critical time steps with line overloading from a time series calculation. For each of the critical time step a load case is created.

A load case is defined by:

- the current switching state,
- complex $S_D$ power demand of loads,
- complex $S_g$ power generation of PQ-controlled generators,
- complex bus voltage set points $V_r$ of reference buses,
- the real power $\Re(S_g)$ in-feed and voltage magnitude $|V_g|$ of PV-controlled generators units, and
- outages of power lines or transformers.
4.2.2 Efficient Power Flow Implementations

In this section two concepts are introduced to reduce the computational time of power flow calculations. First, a method to reduce the conversion overhead of time series simulations. Second, a tailored Newton Raphson (NR) implementation. Both methods are integrated in pandapower version 2.2.

Reducing the Conversion Overhead

The pandapower data structure net [116] is element based in comparison to other tools [54, 150, 151], which are based on a BBM (see Section 3.1.2). An element based data structure has several advantages and allows a convenient modification of the power system model. However, the element based structure needs to be converted to a BBM to calculate PF results. The unknown variables of a PF calculation are the complex bus voltages $V$. From this voltage vector, all other unknown variables are then determined. In pandapower, this is a three-step process. First, intermediate results are written to the internal data format ppc. Second, the NR PF calculation is performed. Third, results are converted back from the ppc to the element based pandapower net. Within a time series simulation, the conversion from and to the BBM accounts for a significant overhead. In most time series simulations this overhead can be reduced since only parts of the inputs vary between two time steps or only some results need to be converted back from the ppc. Therefore, it is possible to bypass the conversion overhead by keeping the BBM in memory while updating the changed values within a time series simulation. Certain constraints must be considered between two time steps:

1. only bus values ($P$, $Q$, $V_m$) change between two time steps. Otherwise, the power injection matrix $S_{bus}$ is re-created,

2. no line/transformer impedances change. Otherwise, the admittance matrix $Y_{bus}$ is re-created, and

3. no switching positions change. Otherwise, $Y_{bus}$ and $S_{bus}$ are re-created.

This concept is implemented in pandapower since version 2.2 [115]. Calculation time savings are around $80\%$ in comparison to the previous implementation (detailed comparisons are shown in Section 5.1.1).
4.2. Time Series Simulation

Efficient Jacobian Matrix Creation

This section adapts material from [117], co-authored by Martin Braun\(^1\).

The use of the published material in this dissertation is permitted.

Many matrices can be kept in memory during time series simulations except the Jacobian matrix \(J\). It must be re-calculated in each NR iteration. The calculation of this matrix is time consuming, especially for systems with more than a few hundred buses. Therefore, the creation of \(J\) requires an efficient implementation. Commonly used open-source implementations [150, 151] determine the Jacobian matrix in each iteration by:

1. calculating the sub-matrices \(\partial|V|\) and \(\partial\delta\) as partial derivatives for every non-slack bus, and

2. creating the Jacobian matrix in compressed row storage (CRS) format by stacking these derivatives matrices.

A tailored implementation of these steps, which exploits the sparsity of the matrices, is presented in this thesis and was first published in [117]. Figure 4.4 visualizes the proposed algorithm. Inputs to the algorithm are the complex admittance matrix \(Y_{bus}\) in the CRS sparse\(^2\) format and the complex voltage vector \(V\). First, several tailored matrix and vector operations are performed on \(Y_{bus}\) and \(V\) to obtain the partial derivatives \(\partial|V|\) and \(\partial\delta\). Second, the real- and imaginary parts of \(\partial|V|\) and \(\partial\delta\) are selected to create the Jacobian matrix. This efficient selection of these entries saves additional computational time.

\(J\) consists of the partial derivatives \(\Delta P\) and \(\Delta Q\) with respect to the voltage angle \(\delta\) and magnitude \(|V|\) [148]. For every PQ-bus the partial derivatives \(\frac{\partial P}{\partial \delta}, \frac{\partial Q}{\partial \delta}, \frac{\partial P}{\partial |V|}\) and \(\frac{\partial Q}{\partial |V|}\) need to be calculated in each NR iteration. For every PV bus, the partial derivatives \(\frac{\partial P}{\partial \delta}\) and \(\frac{\partial Q}{\partial \delta}\) have to be calculated. In the following, it is defined that \(\partial \delta = [J_{11}^T J_{21}^T]\) and \(\partial |V| = [J_{12}^T J_{22}^T]\). The Jacobian matrix is defined as follows:

\[
J = \begin{bmatrix}
J_{11} & J_{12} \\
J_{21} & J_{22}
\end{bmatrix} = \begin{bmatrix}
\frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial |V|} \\
\frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial |V|}
\end{bmatrix} = \begin{bmatrix} \partial \delta & \partial |V| \end{bmatrix}
\] (4.1)

\(^1\)The material is under copyright © 2018-2020 by IEEE.

\(^2\)See Appendix B for details on the CRS-format.
The partial derivatives of the voltage magnitudes \( \partial |V| \) and the voltage angles \( \partial \delta \) are determined by (4.2) and (4.3) [179]. Where \( d() \) is defined as a diagonal matrix of a vector:

\[
\begin{align*}
\partial |V| &= d(V) \cdot (Y_{bus} \cdot d(V_{norm}))^* + d(I^*) \cdot d(V_{norm}) \\
\partial \delta &= jd(V) \cdot (d(I) - Y_{bus} \cdot d(V))^*
\end{align*}
\]

with

\[
\partial \delta, \partial |V| \in \mathbb{C}^{n \times n}
\]

\[
V = \begin{bmatrix} v_1 & \cdots & v_n \end{bmatrix} \in \mathbb{C}^{1 \times n}
\]

\[
I = \begin{bmatrix} y_{11} & \cdots & y_{1n} \\
\vdots & \ddots & \vdots \\
y_{n1} & \cdots & y_{nn} \end{bmatrix} \begin{bmatrix} v_1 \\
\vdots \\
v_n \end{bmatrix} = \begin{bmatrix} i_1 \\
\vdots \\
i_n \end{bmatrix} = Y_{bus} \cdot V \in \mathbb{C}^{n \times 1}
\]

\[
V_{norm} = \frac{V}{|V|} = \begin{bmatrix} v_{norm,i} \end{bmatrix} \in \mathbb{C}^{1 \times n}
\]

Equations (4.2) and (4.3) include several mathematical operations including the matrix dot product, additions and complex conjugations. Implementations of sparse matrix operators iterate over the number of non zero (NNZ) elements of the matrices once for each operation. Equations (4.2), (4.3) and (4.6) require to iterate over
the NNZ elements of the admittance matrix $Y_{bus}$ six times for multiplications, twice for additions and three times for conjugations. In total $11 \cdot \text{NNZ}$ iterations are necessary. The presented tailored algorithm, combines different operations and reduces the number of total iterations down to two iterations over the NNZ elements in $Y_{bus}$. The computational effort is further reduced by only creating the data vectors of $\partial |V|$ and $\partial \delta$, instead of recalculating the row pointers and column indices. Instead, these are copied from $Y_{bus}$. This is possible since the column indices and the row pointer are identical for $Y_{bus}$, $\partial |V|$ and $\partial \delta$. Thus, only the data vectors $\partial V_{m,x}$ and $\partial V_{a,x}$ differ from $Y_x$ and need to be computed to generate the CRS representation of the matrices $\partial |V|$ and $\partial \delta$. With two stacked loops (see listings of pseudocodes B.1 and B.2 in Appendix B), (4.6) is calculated:

$$i_i = \sum_{k=1}^{n} y_{ik} \cdot v_k$$

(4.8)

as well as parts of (4.2) and (4.3):

$$\partial |V_{x,ik}| = y_{ik} \cdot v_{\text{norm},k}$$

(4.9)

$$\partial \delta_{x,ik} = y_{ik} \cdot v_k$$

(4.10)

$$\text{temp}_i = i_i^* \cdot v_{\text{norm},i}$$

(4.11)

With these vectors and two additional loops (see pseudocode B.2 in Appendix B), the data vectors of the derivatives are created:

$$\partial |V_{x,ik}| = v_i \cdot (\partial |V_{x,ik}|)^* + \text{temp}_i$$

(4.12)

$$\partial \delta_{x,ik} = jv_i \cdot (i_i - (\partial \delta_{x,ik}))^*$$

(4.13)

The data vectors $\partial \delta_x$, $\partial |V_x|$ together with the row pointer $Y_p$ and and column indices $Y_i$ represent $\partial |V|$ and $\partial \delta$ in the CRS format. $J$ is filled with parts of $\partial |V|$ and $\partial \delta$. These parts are selected by the index masks $p$ and $pq$, which contain the bus indices of the PV- and PQ-buses of a grid with $N_p$ PV- and $N_{pq}$ PQ-buses. $N_{pvpq} = N_p + N_{pq}$ equals the sum of the number of PV and PQ-buses. The masks are used to select the imaginary and real parts of the matrices $\partial |V|$ and $\partial \delta$ to obtain $J_{11} - J_{22}$:

$$J_{11} = \mathfrak{R}(\partial \delta_{[pvpq,pvpq]})$$

(4.14)

$$J_{12} = \mathfrak{R}(\partial |V|_{[pvpq,pq]})$$

(4.15)
\[ J_{21} = \Im(\partial \delta[pq, pvpq]) \]  
\[ J_{22} = \Im(\partial |V|[pq, pq]) \]  
\[(4.16)\]

The Jacobian has the dimension:
\[ J = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix} \in \mathbb{R} \quad \text{with dimension} \quad \begin{bmatrix} N_{pvpq} \times N_{pvpq} & N_{pvpq} \times N_{pq} \\ N_{pq} \times N_{pvpq} & N_{pq} \times N_{pq} \end{bmatrix} \]  
\[(4.18)\]

The time consuming stacking of the sub-matrices is avoided by creating the row pointer \( J_p \), the column indices \( J_i \) and the data vector \( J_x \) of the Jacobian matrix directly by:

1. counting the total NNZ in \( J \),
2. iterating over the rows of \( J \), which are equal to \( N_{pvpq} \),
3. iterating over the columns \( V_j \) for the row in \( V_p \) for the current bus in \( pvpq \),
4. if an entry exists for the current bus in \( V \), writing an entry for \( J_x \) and \( J_j \), and
5. counting the NNZ entries in current row and adding them to the row pointer \( J_p \).

This is implemented with two for-loops in \texttt{pandapower} (see pseudocode B.3 in Appendix B). In total it is necessary to iterate over the NNZ elements of \( N_{pv} + 2 \cdot N_{pq} \) rows in \( \partial V \). Calculation time comparisons in Section 5.1.1 show that a speed-up of up to 6-30 times is possible in comparison to other open-source implementations.

### 4.2.3 Prediction of Power Flow Results with Supervised Learning

The reduction of the conversion overhead and the creation of the Jacobian matrix reduce the simulation time without a loss in result precision. This simulation time can be further reduced by predicting bus voltages and line loadings with supervised learning models. Supervised learning is a ML task which learns a function that maps an input to an output based on example pairs of inputs and outputs [180]. A
function is then inferred from the labelled training data consisting of a set of training examples [181]. Each training example is a pair of an input object and the desired output value. In this thesis, the input data are the known PF variables, and the outputs are the branch loadings, bus voltage magnitudes or classified time steps. A trained ML model then predicts these results with the inferred function from untrained inputs. The better the function approximation is, the more unseen examples can be correctly labelled. In the context of time-series-based planning, it is the goal to identify time steps with high line loadings or voltage violations for the given input time series. These PF results can either be directly predicted by a regressor or indirectly by training a classifier [110, 118]. The classifier only determines if a time step is critical or not, and PF results must be calculated afterwards. A comparison of the quasi-static PF calculation, the regression method and the classification approach is shown in Fig. 4.5. Inputs to the standard PF calculation and the ML methods are the grid data, time series for load and generation as well as the bus voltage and branch loading limits. Only a sample of all time steps is needed for the regression and classification training. Alternatively, the ML can be trained with a scenario generator if no time series are available for training. The remaining bus voltage magnitudes and branch loadings of the time series are then predicted by the regressor or time steps are classified as critical by the classifier. Optionally, the PF results can be predicted for the critical time steps or validation purposes of the regression results.

**Input Layer Definition**

The same input layer definition is used for the regression and classification methods. Each row of the input layer or feature vector $x_t$ represents a time step $t \in T$ containing all known variables of the PF calculation. A single feature is defined by:

$$x_t = \left[ (|V_r,t|) \ (\delta_r,t) \ (|V_g,t|) \ (P_{bus,t}) \ (Q_{bus,t}) \right] \in \mathbb{R}^{1 \times N_f}$$

with $|V_r|$ the vectors of voltage magnitudes, $(\delta_r)$ the corresponding angles of reference buses, the vector of $|V_g|$ voltage magnitudes for generators, $(P_{bus})$ the real power vectors of $PQ$-buses and $PV$-buses, and $(Q_{bus})$ the reactive power vectors of $PQ$-buses. $N_f$ is the size of each feature vector determined by $N_f = N_r + N_g + 2 \cdot N$, where $N_r$ is the number of reference buses, $N_g$ the number of generators and $N$
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Figure 4.5: Overview of the quasi-static PF, regression and classification methods. Research questions are in dashed boxes (adapted from [118]).

the number of all buses of the power system. These features are stacked to obtain the input layer matrix $X$ for the ML algorithm.

$$X = \begin{bmatrix} (|V_{r,0}|) & (\delta_{r,0}) & (|V_{g,0}|) & (P_{bus,0}) & (Q_{bus,0}) \\ (|V_{r,1}|) & (\delta_{r,1}) & (|V_{g,1}|) & (P_{bus,1}) & (Q_{bus,1}) \\ \vdots & \vdots & \vdots \\ (|V_{r,T}|) & (\delta_{r,T}) & (|V_{g,T}|) & (P_{bus,T}) & (Q_{bus,T}) \end{bmatrix} \in \mathbb{R}^{T \times N_f} \quad (4.20)$$

Constant columns are dropped prior to the training of the model. This reduces the size of the input layer to reduce training time. Several data-preprocessing methods are tested to reduce the training error. Results are discussed in Section 5.1.2.

Output Layers Definition

Different output layers are defined for the regression and classification method. The regressors are trained to predict the voltage magnitudes $|V|$ of all buses and branch loading values $I_{\%}$ of all lines. It can be assessed if a time step is critical by comparing these predictions with the pre-defined limits. The regression output layers $y_{r,1}, y_{r,2}$ are matrices of which each row represents parts of the PF results of one time step $t \in T$. Separate regression models are trained to predict the voltage

Calculation | Outputs
---|---
compute power flow (PF) of all time steps | PF results: $|V|, \delta, I_{\%}$
| multi variable PF results | true violations
computation time for $T \times (N+1)$ computations? | predictions: $|V|, I_{\%}$
compute fraction of time steps | predicted violations
| multi variable prediction | predicted classified violations of each time step
sample size of training time steps? | recall, precision? classification time?
compute fraction of time steps | optional: power flow calculation to validate prediction
| binary classification | evaluation of performance metrics
sample size of training time steps? | accuracy? training & prediction time?
magnitudes $|V|$ in per unit values of all buses and the branch loading values $I\%$ in percent of the maximum allowed current $I_{kA}$.

The classifier predicts whether a time step is critical or uncritical. The classification output layer $y_{\text{classifier}}$ contains the probabilities $p_t$ and $q_t$ with $q_t = 1 - p_t$ and $p_t, q_t \in [0, 1]$. The probabilities $p_t = 0, q_t = 1$ are equal to an uncritical time step and $p_t = 1, q_t = 0$ equals critical. A time step is critical when either the voltage magnitude of any bus is out of boundaries $|V_i| < v_i^{\text{min}}, |V_i| > v_i^{\text{max}}$ or any line loading $I\%$ violates its maximum ($I\% > I_{\%\text{,max}}$).

\begin{equation}
\begin{bmatrix}
    |V_0| \\
    |V_1| \\
    \vdots \\
    |V_T|
\end{bmatrix}
\begin{bmatrix}
    I_{\%0} \\
    I_{\%1} \\
    \vdots \\
    I_{\%T}
\end{bmatrix}
\begin{bmatrix}
    p_0 & q_0 \\
    p_1 & q_1 \\
    \vdots \\
    p_T & q_T
\end{bmatrix}
\end{equation}

\subsection*{Training Data generation}

ML models are limited by the information provided by the training data. The training data creation and its selection and size are one of the essential factors to obtain a robust model. In this thesis, the training data is generated by two methods:

1. based on time series PF results, and
2. with a scenario generator.

Figure 4.6 depicts the two methods for training data generation. Training data from time series is obtained by selecting a random sample of the time series PF results. An alternative to a random selection is to apply different cross validation methods, as explained in Section 3.2.2.

The scenario generator generates a diverse subset of possible scenarios in a grid. By scaling load and generator values, grid states are created, ranging from high load / low feed-in scenarios to high feed-in / low load scenarios in discrete steps. The base scaling value is then multiplied with the nominal power of the generator or load. Gaussian noise is added to each of the resulting power values. The intent
is to create variance in the training data to act as regularization for the ANN, increasing the model’s ability to generalize. A PF calculation per scenario generates the target labels for the ML problem, e.g., the exact voltage magnitudes. Details on the scenario generator are published in [157].

![Training data generation from (a) time series and (b) the scenario generator.]

**Figure 4.6:** Training data generation from (a) time series and (b) the scenario generator.

**Architectures**

In Section 5.1.2 several ML models are compared to identify the most-suitable architecture for the regression and classification tasks. All tested methods are listed in Table 4.1. The methods are selected according to their multi-output capability. A MLP architecture is used for the ANN with 2-3 hidden layers. The hidden layers consist of 100-200 perceptrons with the rectified linear unit (ReLU) activation function. The output layer has a linear activation. Training lasts for max. 800 epochs with a constant learning rate of 0.0008. The training process is performed by Adam optimizer on Central Processing Units (CPUs) or Graphics Processing Units (GPUs) [166]. A randomized search optimizes the hyperparameters. The default parameters for the remaining models are obtained from [164]. A separate model is trained for each $N$-1 case, allowing parallel training on multiple CPUs or GPUs.
Table 4.1: Compared ML architectures for the regression and classification task (+ supports multi output regression/classification, – no support).

<table>
<thead>
<tr>
<th>Architecture</th>
<th>Regression</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>multilayer perceptron (MLP) [164]</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Extremely Randomized Tree (ET) [164]</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Random Forest (RF) [164]</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Decision Tree (DT) [164]</td>
<td>+</td>
<td>–</td>
</tr>
<tr>
<td>XGBoost (XGB) [182]</td>
<td>–</td>
<td>+</td>
</tr>
</tbody>
</table>

4.3 Power System Optimization

The following three sections detail the implemented grid planning optimization strategy. Section 4.3.1 describes the multi-year planning method considering operational flexibility and conventional measures. Section 4.3.2 explains the implementation of the operational optimization. Finally, Section 4.3.3 describes the hybrid optimization implementation to integrate conventional planning measures such as power line replacements.

4.3.1 Multi-Year Planning Method

Long term planning horizons are considered in this thesis by regarding multiple consecutive years. In each year, additional growth of demand, generation, and storage capacity are expected. This growth leads to higher requirements on the infrastructure and ultimately necessitates grid expansion measures such as power line installations. Typical periods for planning, approval and construction of a HV overhead line are about 3-5 years, depending on the length and routing of the line. Power line installations result in high CAPEX for the grid operator ranging from €0.42-1.0 million per kilometer of newly built overhead lines and cables. These installations are designed and maintained for several decades [6]. Efficient control of operational measures allows postponing the installation of new power lines. Controlling operational flexibilities, however, increase the OPEX. The power system operator must decide when to invest in the infrastructure within the planning
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horizon. The question arises at what point it is more economical to invest in infrastructure than to take operational measures, e.g., to curtail RES. To answer this question, a discrete optimization problem is formulated in this thesis with the following assumptions:

- a strong increase of RES is expected in the area of consideration,
- investments in power lines/transformers are necessary in this area in order to guarantee future supply, and
- operational measures are an alternative option to the investment.

In this thesis, a decomposition method is chosen to solve the discrete optimization problem. A separated calculation of operational measures and planning measures in each year enables the power system operator to evaluate several investment paths under different cost assumptions, including the installation costs per kilometer, costs for the curtailed energy and interest rates. The decomposition method is depicted in Fig. 4.7. If the power system operator invests in the infrastructure in the first year, CAPEX of $c_1$ are obtained in the same year. Without an investment, OPEX of $c_1$ are excepted in year one. For each of the two options, two new options are available in year two, leading to four possible combinations of expenditures. Finally, in the last year, $2^Y$ decision paths are obtained, which requires $2^{(Y+1)}$ year simulations in total\(^3\). The optimal path is selected by comparing the NPV of the cash flows in the regarded time horizon. In this thesis, long term CAPEX are compared with short term OPEX with the DCF and the annuity method as detailed in Section 2.1.2. Further details are published in [121].

Equations (4.22) - (4.26) formulate the decision problem. The NPV of cash flows with the interest rate $i_r$ during the planning horizon $Y$ is minimized. In each year $y$, it is assumed that it is either invested in the infrastructure resulting in $C_{CAPEX} \geq 0$ or operational measures are taken resulting in $C_{OPEX} \geq 0$. The two types of expenditures are assumed to be mutual exclusive within one year, which is formulated

\(^3\)Calculating the full tree may lead to long simulation times. A method to reduce the calculation time is to cut the tree into several periods as detailed in Appendix B.
Figure 4.7: Multi-year decision path of a combined optimization for $Y$ years [121].

by (4.23). Technical limits are considered by (4.24) - (4.25) during the optimization.

$$\text{minimize:}$$

$$NPV = \sum_{y=1}^{Y} \frac{C_{\text{OPEX},y} + C_{\text{CAPEX},y}}{(1+r)^y}$$

(4.22)

subject to:

$$C_{\text{OPEX},y} \cdot C_{\text{CAPEX},y} = 0$$

- mutually exclusive option (4.23)

$$v_i^{\text{min}} \leq |V_i| \leq v_i^{\text{max}} \forall i \in N$$

- voltage magnitude limits (4.24)

$$|S_{ij}| \leq s_{ij}^{\text{max}} \forall (i,j) \in B$$

- branch thermal limits (4.25)

$$|I_{ij}| \leq i_{ij}^{\text{max}} \forall (i,j) \in B$$

- branch current limits (4.26)

Figure 4.8 shows a flowchart of the implementation. First, time series for future years are generated considering load, generation, and storage growth. The time series are the input to the simulation of one year, which determines the critical loading situations. Results of the time series simulation are the critical load cases of the currently regarded year. Some thousand load cases can be obtained for a time series in 15 min resolution. These load cases are input to the operational optimization in the second step. Each load case is solved individually by applying operational measures, such as the curtailment of RES, switching-state or tap-changer optimization. The same load cases are input to a second optimization considering only grid expansion measures. This planning optimization consists of two steps. First, the most severe load cases are determined as the basis for planning. Second, the optimization algorithm is started considering only planning measures, e.g., power line/transformer replacements or additional line measures. Planning results for the
current year are the discrete planning measures. The result of the operational and grid planning optimizations are input to the two optimizations of the following year. This process is repeated until the pre-defined planning horizon of $Y$ is analyzed. The result is a decision tree consisting of $2^Y$ solution paths. The optimal investment path is finally obtained by comparing the NPV of all cash flows paths as shown in Fig. 4.7. In the last step, a $N$-1 analysis is performed for the optimal investment path. For each year of the optimal path, it is ensured that no asset overloaddings or voltage violations occur in single contingency cases or if operational measures are able to solve these violations. Results of the optimization process are the applied planning measures of each year as well as the corresponding operational measures. Furthermore, technical limits, losses, and expenditures are evaluated.

**Figure 4.8:** Combined optimization strategy of operational and planning measures (adapted from [121]).

### 4.3.2 Operational Optimization Models

Operational flexibility is considered in the time-series-based planning strategy by implementing simulation models of the corresponding elements, e.g., generators,
4.3. Power System Optimization

tap-changer or storage systems. In \textit{pandapower}, different control methods are implemented as controllers (see Section 4.2.1). Controllers are applied to optimize the load cases by, e.g., reactive power optimization or changing the tap changer position. A tap-changer controller was released with \textit{pandapower} version 2.2. Additional control models are implemented as part of this thesis, including the static curtailment concept, OPF-based curtailment method, and two storage system optimization models.

\textbf{Static Curtailment Method}

The technical regulator for power grids in Germany, VDE|FNN, recommends different implementations for the curtailment of wind and PV-generators. The guideline [28] recommends to allow a curtailment of 3\% of the annual generated energy from PV plants and WPPs in grid planning. The static curtailment method can be applied if time series are available for generators. It is common that the annual generation curve is given in discrete time steps $t$ in, e.g., a 15 min measurement interval. From this curve, a curtailed time series is obtained in several steps. First, the total generated energy $E_g$ of a RES is determined by the sum of generated power $P_t$ over each time step:

$$E_g = \sum_{t=0}^{T} P_t \Delta t \quad (4.27)$$

from which the curtailed energy $E_c$ of $X$\% of the total generated energy is determined by:

$$E_c = X\% \cdot E_g = X\% \cdot \sum_{t=0}^{T} P_t \Delta t \quad (4.28)$$

$E_c$ is also determined by the difference between $E_g$ and the area under the sorted annual generation curve limited by $P_{t_{\text{max}}}$:

$$E_c = E_g - (P_{t_{\text{max}}} \cdot t_{\text{max}} + \sum_{t=t_{\text{max}}}^{T} P_t \Delta t) \quad (4.29)$$

By inserting (4.28) in (4.29), and solving for $P_{t_{\text{max}}}$ one obtains:

$$P_{t_{\text{max}}} = \frac{E_g \cdot (1 - X\%) - \sum_{t=t_{\text{max}}+1}^{T} P_t \Delta t}{t_{\text{max}}} \quad (4.30)$$
This function is iteratively solved with a binary search. The result is a second time series with a limited value of $P_{t_{\text{max}}}$ for the real power injection. This time series data is obtained prior to the time series simulation. Figure 4.9 shows the original time series and the curtailed one (a). $P_{t_{\text{max}}}$ is obtained from the sorted annual curve (b).

![Figure 4.9: Static curtailment strategy. (a) shows the difference between the curtailed time series and the original time series. (b) shows how the maximum real power injection $P_{\max}$ is obtained from the sorted annual curve.](image)

**OPF Curtailment**

A second method to determine the necessary curtailment of RES generators is based on optimization models. OPF calculations allow minimizing the amount of curtailed energy. The OPF optimization requires additional inputs including:

- the grid model,
- annual injection time series for each generator,
- annual price time series for each generator or fixed priced assumptions, and
- an optimization model and solver.

An OPF optimization determines the minimum curtailment for each load case. The curtailed energy is then determined by the sum of the curtailed energy of all violated time steps $T_{\text{viol}}$. An example is shown in Fig. 4.10. The generated power...
$P_{\text{generated}}$ is reduced to $P_{\text{curtailment}}$ by the OPF so that $I_{\text{violation}} \leq 100\%$ which equals the reduced loading $I_{\text{curtailed}}$.

![Diagram](image)

**Figure 4.10:** OPF curtailment strategy. The curtailed energy is determined by curtailing the injection for RES.

The objective of the OPF optimization in one time step is to maximize the power output of the RES generators by extending the standard OPF formulation (see Section 3.3.1) to:

$$\text{minimize: } \sum_{k \in G} f_k(P_{g,k}) - \sum_{i=0}^{G_{\text{RES}}} c_i \cdot P_{g,i}$$

(4.31)

with $c_i$ the cost of the generated energy for the RES generators $G_{\text{RES}}$. The cost is a positive value so that the generated power is maximized and the curtailment minimized. $c_i$ can be the spot market price or a fixed price, depending on the remuneration of the RES generator. The following constraint is added to the OPF formulation to ensure generation limits for the RES generators:

$$P_{k,t}^{\text{max}} \leq P_{k,t} \leq P_{k,t}^{\text{min}}, \forall k \in G_{\text{RES}}$$

(4.32)

$P_{k,t}^{\text{max}}$ is the actual power output of a generator $k$ at time step $t$. Its value is equal to the generated power without curtailment. $P_{k,t}^{\text{min}}$ is the minimum power output at time step $t$ which is usually zero.
Storage System Optimization Models

Two generic storage system models are implemented to model the economically-oriented behaviour of storage system owners. The first model is a price-sensitive model without further grid restrictions. The second model is an optimization model, which is restricted by the thermal line loading limits. The implemented models are generic to allow the simulation of different batteries, for example, stationary batteries or power to gas installations. Figure 4.11 shows an overview of both storage implementations. Input data to both models are the time series for load, generation, and market price or fixed price time series. Outputs of the models are different time series depending on the active constraints. The DC PF constrained storage model considers line loadings in the optimization and the economical storage model neglects the connected power system. Results of the optimization are time series, which are input for the time series simulation. Both models are based on the market-oriented, linear optimization model of [87]. The extension is published in [122].
model is formulated by (4.33)-(4.38). The objective (4.33) is to maximize the revenue of interconnected storage systems, loads and RES connected at the buses $N_s$ over all time steps in $T$. The revenue is determined by the sum of all bus power injections $P_{b,t}$ and the cost $c_{b,t}$ at time step $t$. Constraints to the optimization problem are the charge (4.34), discharge (4.35), and real bus power injection limits (4.36). The bus power injection limits $p^l_t, p^u_t$ depend on load and RES generation. These limits are derived from the input time series for each time step. With (4.37) mutually independent charging and discharging is modelled. Equation (4.38) models compliance with the energy rating limits of the storage system. Considered are the charge and discharge efficiency values $\eta^c, \eta^d$ as well as a constant self-discharge $p_{\text{self}}$ per time step.

maximize:

$$\sum_{b}^{N_s} \sum_{t}^{T} c_{b,t} \cdot P_{b,t}$$

subject to:

$$0 \leq p^c_t \leq p^c_u$$ - charge power \hspace{1cm} (4.34)

$$0 \leq p^d_t \leq p^d_u$$ - discharge power \hspace{1cm} (4.35)

$$p^l_t < P_{b,t} \leq p^u_t$$ - real bus power injection \hspace{1cm} (4.36)

$$p^c_t \cdot p^d_t = 0$$ - mutually exclusive charging or discharging \hspace{1cm} (4.37)

$$e^l \leq e_{t=0} + \sum_{t=1}^{T} \eta^c \cdot p^c_t - \frac{1}{\eta^d} \cdot p^d_t - p_{\text{self}} \cdot e^u \leq e^u$$ \hspace{1cm} (4.38)

with:

$$e^l, e^u$$ - lower and upper energy capacity

$$p^c_u, p^d_u$$ - charge and discharge ratings

$$\eta^c, \eta^d$$ - charge and discharge efficiency

$$p_{\text{self}}$$ - relative self discharge rating

$$p^l_t, p^u_t$$ - real power injection limits
The grid constrained storage optimization model is obtained by adding the maximum branch capacity $p_{ij}^u$ as additional constraints with equations (4.39) and (4.40). A linear model results by considering the real power limits with the DC assumption.

\[-p_{ij}^u \leq \frac{1}{X_{B,ij}}(\delta_j - \delta_i) \leq p_{ij}^u - \text{branch real power limits} \tag{4.39} \]

\[\angle V_r = 0 \ \forall r \in R - \text{reference bus angle limits} \tag{4.40} \]

**Tap-Changer**

Transformer tap-changer regulate the voltage set-point by changing the tap-position in discrete steps (see Sec. 2.2.2). Tap-changer are considered as an operational measure by tap-controller as implemented in *pandapower* version 2.2 [115]. A tap-controller changes the tap-position of a transformer in discrete steps ranging from the minimum and maximum defined tap-position. The tap-position is changed until the voltage at the corresponding transformer side is within the pre-defined limits $v_{i}^{\text{max}}$ and $v_{i}^{\text{min}}$ or if a maximum iteration limit is reached. The tap-controller implementation is not part of this thesis, but compatible to the time series simulation module.

**Reactive Power Compensation**

Reactive power compensation of RES as an operational measure can be considered with pre-defined $\cos \phi$ values, reactive power controller or with OPF calculations. Reactive power controller implementations are not part of this thesis, but compatible to the time series module. The standard OPF formulation (see Section 3.3.1) is applied to optimize the reactive power feed-in of RES. No OPEX are assumed for the provision of reactive power by RES [183].
4.3.3 Hybrid Grid Planning Optimization Strategy

The grid optimization strategy is implemented as a combination of mathematical programming and heuristic methods. Figure 4.12 depicts a flowchart of this hybrid optimization concept. Input to the optimization is the grid data net in the *pandapower* format, load cases for the optimization, the planning constraints, and different sets of binary planning measures. These measure sets include possible power line and transformer replacements $M_L$, additionally installed lines $M_{AL}$, and switching measures $M_S$. First, the mathematical programming method is started to reduce the measure set. The result $M_{MP}$ is input to the heuristic optimization, which further modifies the current solution candidate. The fitness evaluation in several steps determines the fitness of this solution.

**Mathematical Programming**

The mathematical programming optimization determines the set $M_{MP}$, which is a subset of the measures from $M_L$ and $M_{AL}$. The set $M_{MP}$ is empty in the first optimization loop. It is filled with the optimization result $s_{MP}$ after each mathematical programming optimization of power system model net in its current switching state. In [124], it is shown that a DC OPF approximation model is able to determine suitable initial solutions in a short time. The mathematical optimization problem is, therefore, simplified as a DC-model:

\[
\begin{align*}
\text{minimize:} & \quad \sum_{l \in M_L} c_l \cdot \alpha_l + \sum_{al \in M_{AL}} c_{al} \cdot \beta_{al} \\
\text{subject to:} & \quad (P_{g,i} - P_{D,i}) = \sum_{j=1}^{N} B_{ij} (\delta_j - \delta_i) \quad - \text{coverage of system load (4.42)} \\
& \quad P_{g,k}^{\text{min}} \leq P_{g,k} \leq P_{g,k}^{\text{max}}, \forall k \in G \quad - \text{generator real power limits (4.43)} \\
& \quad \angle V_r = 0 \quad \forall r \in R \quad - \text{reference bus angle limits (4.44)}
\end{align*}
\]
Chapter 4. Implementation of the Time-Series-Based Grid Planning Strategy

\[ P_{B,ij} \leq p^u_{ij} \quad \forall (i,j) \in B \] - branch real power limits (4.45)

\[ P_{B,ij} = \frac{1}{X_{B,ij}} (\delta_j - \delta_i) \] - branch real power flows (4.46)

The objective is to minimize the replacement costs \( c_l \) of lines and transformers as well as the cost for additional built lines \( c_{al} \). The DC model is constrained by the real power limits of generators and branches. \( \alpha_l \) is a binary decision variable, which is equal to one if the power line/transformer \( l \) is replaced and zero otherwise. Similarly, \( \beta_{al} \) is one if the additional power line \( al \) is built and zero if not.

**Metaheuristic Optimization**

The output of the mathematical programming optimization is the reduced measure set \( M_{MP} \), which is input to the metaheuristic optimization. The heuristic optimization starts by initializing the current best solution \( s^* \), which is the empty solution with the highest fitness value of \( f_{\{s^*\}} = (5,0) \). The fitness value \( f_{\{s^*\}} \) is defined by a tuple \((l_r,c_a)\). The level \( l_r \) equals the current violated constraint and \( c_a \) equals the optimization cost for the corresponding level. The input measure set \( M \) for the heuristic optimization is the union of all switching measures \( M_S \) and the reduced set of branch measures \( M_{MP} \), determined by the mathematical programming optimization. The solution candidate \( s \) is the union of the input measures \( s_{MP} \) and \( s^* \). During the optimization process, the current fitness value \( f_{\{s\}} \) of the solution candidate \( s^* \) represents the optimization value. The solution candidate \( s \) is applied to the current grid state (net) and its fitness values \( f_{\{s\}} \) is determined. When the fitness value of \( s \) is lower than the fitness value of \( s^* \left( f_{\{s\}} < f_{\{s^*\}} \right) \), it becomes the new current best solution \( s^* = s \). Otherwise, it is further modified by the metaheuristic strategy until the heuristic evaluation limit or the overall time limit is reached. Several metaheuristics strategies can be applied to find a solution. The heuristic planning method based on the ILS metaheuristic is published in [48] and extended by various other metaheuristics in [125]. The optimization problem is formulated as follows:

\[
\text{minimize} \quad \sum_{l \in M_L} c_l \cdot \alpha_l + \sum_{al \in M_{AL}} c_{al} \cdot \beta_{al} + \sum_{sw \in M_S} c_{sw} \gamma_{sw} \quad (4.47)
\]
4.3. Power System Optimization

The cost function (4.47) minimizes the sum of the cost of all applied measures $M$. The sum consists of the costs of replaced lines and transformers (branches) $c_l$, the costs of the additional installed lines $c_{al}$, and the costs for switching operations $c_{sw}$. $\alpha_l$ and $\beta_{al}$ are binary decision variables as defined above. $\gamma_{sw}$ is a binary variable, which is equal to one if the switch $sw$ is opened and zero otherwise.

**Fitness Evaluation**

The fitness evaluation determines if the solution candidate $s$ solves the planning problem without violating any constraints. Constraints to the optimization problem include topological connection (4.48), PF convergence (4.49) of load cases, voltage magnitude limits (4.50), and branch loading limits (4.51). Different optimization levels are analyzed in each fitness evaluation in a predefined order. First, the topological constraint (4.48) ensures that a connected component within a defined area exists and that no bus is disconnected from the reference bus ($N_d = 0$). Second, the convergence constraint (4.49) is not violated when the PF calculation converges for all load cases $N_{lc}$. Voltage magnitude limits are evaluated by (4.50) and branch loading limits by (4.51). The solution candidate $s$ is a feasible solution to the planning problem when no constraint is violated:

\begin{align*}
N_d &= 0 \quad \forall i \in N \quad (4.48) \\
|l_{c_{\text{convergence}}} &= 1 \quad \forall l_{c} \in N_{lc} \quad (4.49) \\
v_i^{\text{min}} &\leq |V_i| \leq v_i^{\text{max}} \quad \forall i \in N \quad (4.50) \\
|S_{ij}| &\leq s_{ij} \quad \forall (i, j) \quad (4.51)
\end{align*}
Chapter 4. Implementation of the Time-Series-Based Grid Planning Strategy

Figure 4.12: Hybrid optimization strategy.
5 Validation, Comparison and Results

In this chapter, the developed methods are validated on four benchmark systems and applied in a case study based on a real power system. The chapter is divided into three parts: Section 5.1 validates the implemented time series calculation methods. Section 5.2 compares the developed hybrid planning strategy with four metaheuristics and three mathematical programming methods. All methods are validated on four open-source benchmark data sets. Based on these findings, the most suitable methods are identified to be applied in the case studies in Section 5.3.

Benchmark Grid Datasets

All benchmark grids are based on real power systems. Additionally, the grid data, time series and scripts are publicly available as an open-source benchmark dataset to reproduce results [184]. Figure 5.1 shows the topologies of the benchmark grids.

The benchmark cases are modified versions from [116, 146, 184, 185]. The number of available line replacements (REPL), switches (OTS) and expansion planning measures (IAL) determines the complexity of the planning problem. These measures are relevant in Section 5.2. Each optimization chooses from $2^M$ combinations of these measures. Constraints are defined by upper and lower voltage limits as well as line loading limits (PF constraints). Additionally, all buses must be connected to at least one slack or generator bus (topology constraint). Benchmark case (a) Brigande [184] is a meshed German 110 kV urban grid with 17 stations based on a real grid topology. It has the fewest lines and substations. The time
series are in hourly resolution resulting in 8760 time steps while 17 lines define the replacement and switching state optimization (SSO) problems complexity. The installation of additional lines (IAL) measures include 11 new lines. The assumed scenario to benchmark the time series prediction has 1.6% critical time steps and 7.2 km of overloaded lines in total, which are relevant for Section 5.1.2. The characteristics of the SB grids [185] are typical for German meshed high-voltage grid topologies. Time series are available in 15 min resolution with 35 136 time steps in total. The SB mixed case is a meshed 110 kV grid with 64 substation buses and 95 lines to be reinforced. 81 additional lines for the IAL problem are defined. 1.2% of time steps are critical in the base case without \( N-1 \) outages. 12% of the total line length exceeds the loading limit in the given time series. The SB urban case is a meshed 110 kV grid with 82 substations. It has 113 lines with switches as available measures to solve the replacement and SSO problem. 136 additional lines are defined. 1.8% of time steps are critical and 1.8% of lines overload in these time steps. The RTS case [146] is a North American power system model with a time series resolution of 5 min, resulting in 105 408 time steps. It has 73 buses with 104 lines, and 94 additional lines are defined to solve the IAL problem. Only 0.6% of time steps are critical due to 15.8% of overloaded power lines. Table 5.1 lists the relevant data of the three test cases. The IAL measures are obtained from a Delaunay triangulation as proposed in [49].
Table 5.1: Overview of benchmark grid data and relevant time series simulation results.

<table>
<thead>
<tr>
<th></th>
<th>Brigande [184]</th>
<th>SB mixed [185]</th>
<th>SB urban [185]</th>
<th>RTS [146]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_r$ [kV]</td>
<td>110</td>
<td>110</td>
<td>110</td>
<td>230</td>
</tr>
<tr>
<td>$N_{bus}$</td>
<td>17</td>
<td>64</td>
<td>82</td>
<td>73</td>
</tr>
<tr>
<td>$N_l$</td>
<td>18</td>
<td>95</td>
<td>113</td>
<td>104</td>
</tr>
<tr>
<td>$N_{time steps}$</td>
<td>8760</td>
<td>36136</td>
<td>36136</td>
<td>105408</td>
</tr>
<tr>
<td>$N_B$</td>
<td>18</td>
<td>95</td>
<td>113</td>
<td>104</td>
</tr>
<tr>
<td>$N_{sw}$</td>
<td>18</td>
<td>95</td>
<td>113</td>
<td>104</td>
</tr>
<tr>
<td>$N_{al}$</td>
<td>11</td>
<td>81</td>
<td>136</td>
<td>94</td>
</tr>
<tr>
<td>critical time steps [%]</td>
<td>1.6</td>
<td>1.2</td>
<td>1.8</td>
<td>0.6</td>
</tr>
<tr>
<td>overloaded lines [km]</td>
<td>7.2</td>
<td>130.0</td>
<td>14.0</td>
<td>383.0</td>
</tr>
<tr>
<td>overloaded lines [%]</td>
<td>6.2</td>
<td>12.0</td>
<td>1.8</td>
<td>15.8</td>
</tr>
</tbody>
</table>

5.1 Validation of Time Series Calculation Methods

Reducing the calculation time of time series simulations is relevant in industrial applications. Two methods to reduce this calculation time are outlined in Section 4.2.2. Results of these methods are shown in Section 5.1.1. Furthermore, Section 5.1.2 shows results for the ML models when predicting bus voltages and line loadings.

5.1.1 Reduction of Simulation Time of Power Flow Calculations

When calling the pandapower PF function, pandapower converts the grid data from the pandapower structure to a BBM. This conversion process uses about 25% of the total calculation time. Similarly, another 25% of the time is needed to read the
results from the BBM to the *pandapower* structure. The remaining time is needed for the actual NR iterations. Within time series simulations the admittance matrix and other arrays of the BBM can be kept in memory between two time steps to reduce the conversion overhead and save calculation time. Figure 5.2 shows timings with and without the conversion overhead for the four benchmark grids and a time series loop with 8760 time steps. The conversion time from and to the *pandapower* data-structure is significantly reduced without re-calculating several matrices. Only 16.4 –21.6 % of the unoptimized calculation time is needed to calculate the results in the given examples. The majority of time is saved by keeping the admittance matrix in memory and converting the results from the BBM to the *pandapower* structure once at the end of the time series calculation. The remaining conversion time from the *pandapower* structure to the BBM is needed to sum element values to PQ-values. Without the conversion overhead, the majority of time is needed to create the Jacobian matrix $J$ and solve the resulting linear system. Additionally, the solving time is reduced by initializing the voltage vector in a time step with results from the previous time step.

![Figure 5.2](image.png)

*Figure 5.2:* Calculation time for a time series loop with 8760 time steps on a consumer laptop for the benchmark grids with conversion overhead (a) and with less overhead (b).

The calculation time of PF calculations is further reduced by improving the NR implementation (see Section 4.2.2). Since the Jacobian matrix $J$ has to be re-calculated in each NR iteration, a reduction of calculation time is possible by a tailored implementation of the Jacobian creation. The algorithm is integrated into *pandapower* and was first published in [117]. The open-source tools MATPOWER
[150], PyPower [151], and pandapower [116] use a similar BBM on which the PF calculation is performed. This allows a comparison of the tailored implementation in pandapower and the remaining methods. Figure 5.3 shows timings of the tailored method (pandapower) and results when calculating the same grids in matpower and pypower. The speed-up increases with larger grid sizes ranging from 0-6 times in comparison to MATPOWER and 18-30 times in comparison to PyPower.

![Figure 5.3](image)

**Figure 5.3:** Timings on a consumer laptop to calculate (a) \( \partial |V|, \partial \delta \) and (b) the Jacobian matrix \( J \) (adapted from [117]).

### 5.1.2 Prediction of Time Series Simulation Results

A reduction of the computational effort in time series calculations is possible by applying state-of-the-art ML methods. In this section, multiple regression and classification methods are trained to either predict multi variable results or for the binary classifications of time steps\(^1\). The goal is to identify critical loading situations of time series simulations without a high loss in result accuracy. In the following comparison, it is shown which regression and classification methods from [164,182] are most suitable for the prediction of bus voltages, line loadings, and critical loading situations. First, the different regression and classification methods are compared separately. The best methods are identified, which are then compared to identify the method with the lowest prediction error.

\(^1\)This section adapts material from [118], co-authored by Jan-Hendrik Menke and Martin Braun.
Regression Results

Four regression methods are compared including MLP, ET, DT, and RF from [164]. These methods are suitable for multi-output regression as needed when prediction multiple bus voltage magnitudes or line loading values. Results are shown for the SB grids and the RTS test cases. The comparison criteria include:

1. the mean and max. absolute prediction error as defined in Section 3.2.1,
2. the required training size, and
3. the overall training and prediction time.

First, the decrease in the mean prediction error of bus voltage magnitudes and line loadings with more training data is compared. For this, the PF results for one year are calculated in a time step resolution of 35,136 (SB) or 105,048 (RTS). The training data and test data are selected randomly by a shuffled train/test split based on the time series results. The absolute prediction error is evaluated on the test data only. Figure 5.4 shows the mean prediction error for the SB test cases (left) and the RTS test case (right) with increasing training size. All regression methods improve with larger training sizes as expected. The prediction error strongly reduces with training sizes up to 10% of the year simulation results. Larger training sizes reduce the prediction error mainly for the MLP and DT regression methods. The comparison shows that at least 10% of the PF results should be trained when applying a random train/test split. In the following comparisons, a train/test split of 0.1/0.9 is applied. This means that by training with 10% of the year simulation results, 90% of the remaining results are predicted.

Figure 5.5 (a) shows the prediction error of all \(N-1\) cases and 90% of the time steps being predicted. The lowest mean error values for voltage and line loading predictions yield the MLP, ET and RF regression methods. The mean error values of the most accurate method (MLP) is about one third of the remaining methods. When regarding the maximum error in Fig. 5.5 (b), the MLP has the lowest error values. However, it needs a longer training time (c) in comparison to ET and DT. The time needed to predict the PF results (d) is shorter for the DT and MLP methods in comparison to RF and ET. The results show that the MLP has the lowest mean
and absolute error with decent training and low prediction times. With 10% of all time steps being trained and 90% predicted, the mean errors of the line loadings are less than 0.25% for the SB grids and 0.5% for the RTS grid. The error is less than 2% for 99% of the predicted values for SB and less than 5% for the RTS grid. Voltage magnitude prediction errors are low with a mean value of 0.01% and 0.5% in the 99% range for SB and 0.05% (mean) and 0.5% (99%) for RTS. Some rare outliers cannot be predicted with this accuracy as shown by the maximum error in Fig. 5.5 (b).

**Classification Results**

An alternative to predict the voltage magnitudes and line loadings is to predict whether a time step is critical or not. In the following comparisons four classifiers are compared, namely: XGB from [182], RF, ET, and MLP from [164]. In [118], additional classifier including Adaptive Boosting, Gaussian Naive Bayes, and k-Nearest Neighbors (k-NN). Adaptive Boosting and Gaussian Naive Bayes were tested but had, on average, a much lower accuracy in comparison. Their percentage of correct predictions was less than 90% in all test cases. The prediction by the k-NN classifier took between 30 s and 1 min on average in comparison to less than 0.5 s by the other classifiers. Therefore, results are excluded from the following comparison.
5.1. Validation of Time Series Calculation Methods

The most important metrics for the evaluation of the classifiers are the FN values, measured by recall and accuracy, as explained in Section 3.2. Figure 5.6 (left) shows the accuracy and number of FN predictions with increasing training size. The ET and RF method correctly classify 96 – 98% of time steps. The amount of FN predictions are between 1.0 – 1.5%. The MLP and the XGB method outperform both classifiers. These have an accuracy starting at 98% at a training size of 1% being trained. With an increasing training size, the MLP and XGB achieve an accuracy of 99.5% with 0.3% of FN classifications. The training size is 50% of all time steps and $N-1$ cases being trained. Figure 5.6 (right) depicts the corresponding training and prediction times.

The ET and RF classifiers need on average a shorter training time (< 0.7 s with 50% training data) compared to the MLP and XGB methods. The MLP training time takes ~ 2.5 s for 1% of the data up to more than one minute for the RTS test case. The XBG needs the shortest time for training and is twice as fast in the RTS case with 0.9 s and 35 s respectively. Prediction times of the ET and RF
methods are about one third compared to the other methods. Similar predictions time are measured for the MLP and XGB methods with an exception in the RTS case. For this case, the XGB method needs twice the time (∼0.5 s) of the MLP (∼0.25 s).

The training data is highly imbalanced when training with time series data since only a few time steps belong to the critical class. The question arises if the error decreases by applying oversampling techniques, such as SMOTE [161]. SMOTE allows balancing the training data by interpolating between existing samples to create additional samples. The obtained artificial dataset is then applied in training. Figure 5.7 evaluates the difference in recall, precision and accuracy for the MLP classifier with and without oversampled data. Each boxplot contains the classification results of all \( N-1 \) cases and grids combined. An increasing recall value shows an improvement on the FN predictions as expected. However, accuracy and precision decrease. The absolute number of FN predictions decrease by 10.3\% (SB mixed), 33.0\% (SB urban), and 46.1\% (RTS) for a prediction threshold of 0.2. As outlined in 4.2.3, the classification output layer contains the probability \( p_{t} \) of a time step being critical. A probability of \( p_{t} = 0 \) means that the classifier is certain that the time step is uncritical whereas \( p_{t} = 1 \) equals a critical time step. Choosing a lower prediction threshold for \( p_{t} \), therefore, leads to the desired increase in recall but to a decrease in precision and accuracy as shown in Fig. 5.7. The resulting increase of FP predictions is 10.8\%, 23.7\%, and 27.1\% respectively. The threshold

**Figure 5.6:** Classification accuracy and false negative rate (FNR) with increasing training size for all test cases including \( N-1 \) predictions (left). Training and prediction times for each classifier and test case (adapted from [118]).
is a hyperparameter and choosing a suitable threshold depends on the dataset. Based on this comparison, a threshold of 0.2 is applied for the following comparisons. An additional PF calculation for verification is needed for each FP prediction leading to longer simulation times. As explained in Section 3.2.1, the most important metric in the prediction of bus voltage magnitudes and line loadings is the recall metric. A higher recall is equal to fewer FN predictions, meaning that fewer critical time steps are missed. A lower precision can be tolerated since a rather longer simulation time is accepted from additional FP predictions. An accuracy of 1.0 is equal to no prediction error at all and is hardly achievable in real applications.

Figure 5.7: MLP training with and without oversampling (adapted from [118]).

Comparison of the Classification and Regression Methods

The classification and regression methods are both able to predict critical time steps. A direct comparison of both methods allows to identify the most suitable method for PF predictions. For this comparison, the results of the regression method are categorized to compare the classification and regression method. A time step is classified as critical for each (predicted) line loading value above a threshold of the max. loading limit \( I_{\text{limit}} \). The reduction of the line loading prediction limit is similar to setting a lower threshold for the classification probability. Figure 5.8 directly compares the MLP regression and classification in terms of recall,
precision and accuracy. The oversampling method is applied for the classification method since it showed the highest recall values. The regressor prediction has a much higher recall score than the classifier, even when applying oversampling for the classifier. A recall value of nearly one is achieved when setting the prediction limit to a value of \(0.94 \cdot l_{\text{limit}}\) for the regression method. At this threshold, nearly no false negative predictions are obtained. The accuracy is, on average, very high with more than 97% of critical time steps being correctly identified. As expected, higher recall values lead to a drop in the precision to low values in that case, and accuracy decreases to mean values of less than 98%. The precision and accuracy of the regressor significantly increase when setting a \(0.98 \cdot l_{\text{limit}}\) threshold value. Recall drops slightly when increasing the threshold, which means that some critical time steps are not predicted correctly.

![Figure 5.8: Comparison of classification and regression results for the MLP models (adapted from [118]).](image)

Table 5.2 lists further detailed comparisons. The regression method shows better results when applying the thresholds of 0.2 (classifier) and 0.96 \(l_{\text{limit}}\) (regressor). The predictions have lower FN and FP values, a higher accuracy, lower false positive rates (FPRs), and lower FNRs. The FNR is equal to the share of critical time steps that could not be identified. Higher FPRs are equal to the mislabelled uncritical time steps which increase the overall computational time. For each FP prediction, an additional PF calculation is needed to validate the prediction. Between 0.0 – 0.48% are not correctly identified by the regressor when regarding all critical time steps and \(N-1\) case predictions. This share is about half the amount of the classifier. The FPRs of the regressor are between 2.01 – 3.14% in comparison to 2.41 – 8.14% of the classifier.
5.1. Validation of Time Series Calculation Methods

Table 5.2: Comparison of MLP regression and classification results on untrained data \((x^L = \text{lower is better, } x^H = \text{higher is better})\). Classification threshold = 0.2, regression threshold = 0.96 \( \cdot I_{\text{limit}} \) (taken from [118]).

<table>
<thead>
<tr>
<th></th>
<th>SB mixed</th>
<th>SB urban</th>
<th>RTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN classification(^L)</td>
<td>3845</td>
<td>5209</td>
<td>460</td>
</tr>
<tr>
<td>FN regression(^L)</td>
<td>1986</td>
<td>2967</td>
<td>0</td>
</tr>
<tr>
<td>FP classification(^L)</td>
<td>45 617</td>
<td>70 707</td>
<td>552 500</td>
</tr>
<tr>
<td>FP regression(^L)</td>
<td>40 854</td>
<td>45 446</td>
<td>213 010</td>
</tr>
<tr>
<td>correct classification(^H)</td>
<td>2 263 178</td>
<td>2 657 204</td>
<td>6 403 968</td>
</tr>
<tr>
<td>correct regression(^H)</td>
<td>2 269 800</td>
<td>2 684 707</td>
<td>6 743 918</td>
</tr>
<tr>
<td>total classification</td>
<td>2 312 640</td>
<td>2 733 120</td>
<td>6 956 928</td>
</tr>
<tr>
<td>total regression</td>
<td>2 312 640</td>
<td>2 733 120</td>
<td>6 956 928</td>
</tr>
<tr>
<td>FPR classification(^L)</td>
<td>2.41 %</td>
<td>3.13 %</td>
<td>8.14 %</td>
</tr>
<tr>
<td>FPR regression(^L)</td>
<td>2.15 %</td>
<td>2.01 %</td>
<td>3.14 %</td>
</tr>
<tr>
<td>FNR classification(^L)</td>
<td>0.92 %</td>
<td>1.11 %</td>
<td>0.27 %</td>
</tr>
<tr>
<td>FNR regression(^L)</td>
<td>0.48 %</td>
<td>0.63 %</td>
<td>0.00 %</td>
</tr>
<tr>
<td>accuracy classification(^H)</td>
<td>97.86 %</td>
<td>97.22 %</td>
<td>92.05 %</td>
</tr>
<tr>
<td>accuracy regression(^H)</td>
<td>98.15 %</td>
<td>98.23 %</td>
<td>96.94 %</td>
</tr>
</tbody>
</table>

Calculation Time

Table 5.3 compares the timings, including the time needed to compute the training data which are PF results of the base case and \(N\)-1 cases. No parallel computing is applied, which would reduce the calculation time further. For the SB cases, the PF calculation times are between 2.29 h and 2.81 h on a modern desktop PC with panda-power. A longer simulation time of nearly 8 h is needed for the RTS case. This long simulation time is due to the higher resolution of the time series (5 min) in comparison the SB cases. The total training time of the MLP takes 11 – 22 min and between 10 – 20 s for each \(N\)-1 case. The MLP prediction times are much lower with a few hundred milliseconds per \(N\)-1 case and 10-20 s in total. As previously shown, training with at least 10 % of PF results from all time steps and \(N\)-1-cases is recommended.
In total, the overall time needed for the regression and classification method is dominated by the time needed to compute the training data. The overall time can be reduced by parallel computing for every $N-1$ case.

<table>
<thead>
<tr>
<th></th>
<th>SB mixed</th>
<th>SB urban</th>
<th>RTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(N + 1) \cdot T$ PF results [s]</td>
<td>8244</td>
<td>10 116</td>
<td>28 620</td>
</tr>
<tr>
<td>10% of PF results [s]</td>
<td>822</td>
<td>1014</td>
<td>2863</td>
</tr>
<tr>
<td>MLP regressor training avg.* [s]</td>
<td>660</td>
<td>780</td>
<td>660</td>
</tr>
<tr>
<td>MLP regressor prediction avg.* [s]</td>
<td>6.6</td>
<td>7.8</td>
<td>16.5</td>
</tr>
<tr>
<td>MLP regressor sum avg.* [s]</td>
<td>1489</td>
<td>1802</td>
<td>3540</td>
</tr>
<tr>
<td>MLP classifier training avg.* [s]</td>
<td>660</td>
<td>936</td>
<td>1320</td>
</tr>
<tr>
<td>MLP classifier prediction avg.* [s]</td>
<td>16.5</td>
<td>20.4</td>
<td>19.8</td>
</tr>
<tr>
<td>MLP classifier sum avg.* [s]</td>
<td>1499</td>
<td>1970</td>
<td>4203</td>
</tr>
</tbody>
</table>

**Training from Scenario Generator Data**

The previous comparisons show that the classification of time steps in *critical* and *uncritical* is not faster or more accurate than the regression method. Another advantage of the regression method is that bus voltage magnitudes $V_m$ and line loadings $I_{\%}$ are outputs of the multi-variable prediction instead of a binary classification. An additional PF calculation is needed after the classification of time steps to obtain all PF results. In the following comparisons, the MLP regression method is further improved in order to predict the PF results of the year-simulation. As previous results show, the MLP architecture can predict PF results for a given time series with the highest accuracy of all compared methods.

In the previous comparisons, a sample of the time series results was used as training data. An alternative training method is to generate training data with a scenario
5.1. Validation of Time Series Calculation Methods

generator, as proposed in [157]. With an information rich dataset, the ANN interpolates between the trained scenarios and to estimate the system variables with high precision. As explained in Section 4.2.3, the scenario generator scales the load and generation values in discrete steps. Three different scaling parameters are considered regarding the bus power injections: the load, RES generator power, and the variation of fossil-fueled power plant outputs. Each scenario consists of a tuple of scaled values with ranges between 0% and 100% of the maximum power. All units are individually scaled, and Gaussian noise is added to account for variability among the individual units of the same type. For the comparison with time series training samples, the same number of training samples are generated with the scenario generator as applied for training with the time series data (10% of all time steps). Figure 5.9 compares the prediction error when generating training data with the scenario generator and when 10% of the time series results are trained. The maximum error of the voltage prediction significantly decreases with the scenario generator training. The maximum line loading prediction error is rather constant for the SB grids and decreases only for the RTS case. However, an increase of the mean errors can be seen except for the voltage predictions in the RTS case.

Figure 5.9: Training of the MLP architecture with scenario generator data and from time series data (adapted from [118]). (a) shows the max. and (b) the mean absolute error.

The reduction of the max. errors and the increase of the mean errors are explained by the similarities of the training data set to the test data set. The majority of
samples of the time series training data set is more similar to the test data set, leading to lower mean prediction errors. However, the time series training data set contains fewer outliers, showing an increase of the maximum error. In comparison, the scenario generator creates a more balanced training set with fewer outliers that are equally distributed. The comparison of the two training methods further proves that the ANN architecture generalizes well from training data of the scenario generator. No time series are necessarily needed for training since both training methods yield accurate results.

5.2 Comparison of Grid Planning Optimization Methods

In this section, four metaheuristics, three mathematical programming methods, and the proposed hybrid method are compared. The goal is to identify the most suitable optimization method for grid planning and to show the performance of the hybrid method. First, the metaheuristics are compared in Section 5.2.1. Section 5.2.2 validates the hybrid method. Optimization results of the best metaheuristic and three mathematical programming models are the baseline for this optimization.

5.2.1 Comparison of Metaheuristics

The following comparison is based on the metaheuristic framework of [48], which is extended to be compatible with additional metaheuristics as published in [125]. Additional results comparing over 2400 optimization problems for eight different grids are shown in [125]. The following comparison summarizes the results. The added metaheuristics include biologically inspired optimizer, such as GA [39–41], GWO [50, 51] and other methods, e.g., FWA [52, 53]. Open-source implementations of these metaheuristics are integrated from [186–188]. Each metaheuristic searches the solutions space according to its optimization strategy and can be classified in either exploratory or exploitative. Exploratory algorithms evaluate solutions in the unexplored solution space, allowing to escape local optima but require
more time to find the first solution. An example is the GA, which can compare many solutions by mutation. Exploitative algorithms search in the direction of improving solutions. They often converge to local optima. Examples are the greedy HC algorithm and the ILS implementation.

For the following comparison, each algorithm is started 30 times for line replacement (REPL) and the installation of additional lines (IAL) problems on the benchmark grids. Violated grid states (load cases) are generated by randomly scaling load and generation between 50\%-100\% of their maximum value. PF limits are evaluated before the optimization to ensure that the initial conditions are suitable for optimization. Either line loading limits or voltage constraints must be violated. In total, 30 load cases for each grid and a total of 120 different optimization problems are obtained. The input data for each optimization run consists of the power system data, the available measures, and the load case to be solved. Figure 5.10 shows the results for each of the 30 runs per algorithm and grid.

![Figure 5.10: Normalized costs of all 30 runs for the REPL and IAL optimization problems. ILS finds the solutions with the lowest costs in all runs.](image)

The optimization cost in each run is normalized by dividing the solution by the best found solution of all optimizers. Only the results in which all optimizers found a solution are compared. For the RTS case, the ILS heuristic finds solutions for all load cases. For this grid results are compared in 14/30 runs (REPL) and 7/30 runs for the IAL problem. In all runs, the ILS algorithm finds the solution with the lowest cost for the line replacement (“REPL”) and additional line (“IAL”) problem. Run
times until the best solution was found are shown in Fig. 5.11. In most runs, the ILS algorithm needs shorter run times than the remaining heuristics. The ILS is the only heuristic which is able to find switching states (“SSO”) without violated constraints.

**Figure 5.11:** Runtime comparison of metaheuristics until the best solution is found.

Figure 5.12 shows an exemplary run of the REPL optimization to highlight how ILS improves with more iterations. GA, GWO and FWA improve faster with fewer evaluations but eventually get stuck in local optima in most runs. The ILS algorithms needs longer run times to find a first solution, visible in the SB urban case, but the costs steadily decrease with more evaluations.

**Figure 5.12:** Exemplary improvement of each metaheuristic with more evaluations. The ILS typically needs longer to find a first solution, but rapidly improves with more evaluations.
A reason for the worse results of the GA, GWO and FWA algorithms are the higher shares topology evaluations in comparison to the ILS. These evaluations result in invalid switching states in most evaluations. This is one of the main reasons ILS performs better in the comparison, even though the topology evaluations need significantly less computational time than PF evaluations (see Appendix B for details). From this comparison and the results published in [125], the following conclusions are drawn:

- The greedy heuristic, ILS, finds solutions with the lowest average costs for the analyzed benchmark cases. The ILS algorithm often needs longer run times to find the first solution.

- Exploratory heuristics, e.g., GA, GWO and FWA need shorter run times to find the first solution. However, many grids states are evaluated with topology violations without significant improvement during the switching state optimization.

- The initial switching state is essential for convergence. Initialization with random spanning trees, as shown in [125], helps to find valid initial switching states.

No metaheuristic implementation is found, which can find lower cost solutions than the HC and ILS methods from [48] in the same run time for the analyzed grids, load cases and optimization tasks. However, further research is needed to improve the GA, GWO and FWA implementation. In the following comparison, the ILS heuristic is compared to mathematical programming methods. The remaining heuristics are not further regarded.

### 5.2.2 Validation of the Hybrid Strategy

This section adapts material\textsuperscript{2} from [124], co-authored by Alexander Scheidler and Martin Braun. The use of the published material in this dissertation is permitted.

The different optimization strategies are compared in terms of:

\textsuperscript{2}The material is under copyright © 2020 by IEEE.
1. convergence and AC feasibility of the solution,

2. cost of the solution,

3. and run time.

For each of the four benchmark grids, over 100 load cases are created by a probabilistic scaling of generation and load. The scaling of all generators/loads are randomly chosen to be between 50\%-100\% of their maximum value in each load cases. In total, 520 optimization cases are analyzed to have a great variety of loading situations. First, the settings for optimization methods are described. Second, the optimization problems SSO, REPL, and IAL are separately compared. Based on this comparison, a combined optimization of REPL and switching measures is shown. The best optimization method is determined and applied in the final case study of this thesis. The following results and further detailed analysis were first published in [124].

Metaheuristic methods are based on the repeated solving of the steady-state AC PF calculation. In comparison to these strategies solve mathematical programming methods, an optimization problem where the PF equations are boundary conditions. State-of-the-art solvers are often unable to determine solutions for the AC formulation for realistic grid sizes. One solution strategy is to relax the boundaries of the boundary conditions to obtain a convex solution space. Examples are the quadratic SOC relaxation or the linear DC approximation. In the following comparisons, the ILS metaheuristic is compared to the mathematical programming models \textit{ACPPowerModel}, \textit{SOCWRPowerModel} and \textit{DCPPowerModel} implemented in PowerModels.jl [54] (see Section 3.3.2 for details). Different solvers can be applied depending on the relaxation/approximation model. In this thesis, the open-source solver Juniper [189] together with Ipopt [190] and Cbc [191] are applied for the \textit{ACPPowerModel}. This combination of solver and model is referred to as \textit{ACP} in the following comparisons. To solve the \textit{DCPPowerModel} and the second-order cone relaxation \textit{SOCWRPowerModel} Gurobi [192] (REPL, IAL) or Juniper in combination with Gurobi and Cbc (SSO) is applied. These combinations are referred to as \textit{DCP} and \textit{SOCWR}. The hybrid method is a combination of the mathematical programming approach and the ILS metaheuristic. Table 5.4 lists an overview of all methods.
### Table 5.4: Overview of the compared optimization methods.

<table>
<thead>
<tr>
<th>abbr.</th>
<th>complexity</th>
<th>solver</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOCWR</td>
<td>quadratic relaxation</td>
<td>Gurobi (REPL, IAL) or Gurobi + Cbc (SSO)</td>
</tr>
<tr>
<td>DCP</td>
<td>linear DC approximation</td>
<td>Gurobi (REPL, IAL) or Gurobi + Cbc (SSO)</td>
</tr>
<tr>
<td>ACP</td>
<td>non-linear AC-model</td>
<td>Juniper + Ipopt + Cbc (IAL, REPL, SSO)</td>
</tr>
<tr>
<td>ILS</td>
<td>non-linear AC-model</td>
<td>metaheuristic</td>
</tr>
<tr>
<td>HYBRID</td>
<td>non-linear AC-model</td>
<td>combination of DCP model and ILS</td>
</tr>
</tbody>
</table>

### Convergence

First, it is compared in how many runs each algorithm converges and if the solution is valid (AC-feasible). Results are separately listed according to the different optimization problems. Note that the DC and SOCWR power model may converge, but limits may still be violated when calculating the AC PF result. The AC feasibility of a solution is ensured by running an AC PF based on the optimization result. This power calculation validates that the line loading and voltage magnitudes are within their limits. A solution is only valid when it is AC feasible. Figure 5.13 shows the ILS and hybrid strategy can solve more SSO optimizations than the mathematical optimization methods. The DCP converges in more cases than the SOCWR and the ACP model. However, about 80% of the DC solutions are not AC feasible. Regarding the IAL and REPL optimization, all methods, except ACP, converge in nearly all runs. The DCP solutions are not AC feasible in 25% of the cases, and the SOCWR solutions are not feasible in about 45% of runs. Only the ILS and hybrid methods find valid solutions in over 98% of all runs.

### REPL optimization

Table 5.5 lists the results of the REPL optimization. Included are the number of solutions found (N), the average values (M) of the replaced line length, and the time needed to find this solution. The standard deviation (SD) of the average values is given. The ILS and hybrid method converge in the majority of cases. In comparison, the mathematical programming methods do not converge as often, especially...
in the RTS case. For this case, the ACP, SOCWR, and DCP found solutions in less than 16.1%, of all runs, whereas the ILS and hybrid method find solutions in over 87%. The mathematical programming models show better results in the other test cases. As indicated by an asterisk, costs, in terms of shorter line lengths, are only comparable when solutions are found in all runs. For the Brigande case, the hybrid method finds the best solutions on average. For the SB cases, the ILS and hybrid methods find similar replaced line lengths. However, the hybrid method needs significantly less time to obtain these solutions. Insufficient comparable solutions were found in the RTS case.

**Combined Optimization of the SSO and REPL problems**

Table 5.6 lists the results of a combined optimization of switching and line replacement measures for the benchmark grids. Such a combined optimization is applied in the following case study. The hybrid method has, on average, lower costs as shown by the results. However, there is only a small difference in costs indicating that the ILS and hybrid methods find similar solutions in most runs. The most significant advantage of the hybrid method is a shorter run time while finding similar or better solutions than the ILS. Additionally, the hybrid method converges for the largest test case (RTS). Here, the ILS method is not able to find a single solution in a combined optimization of REPL and switching measures. The reason is that the vast solution space, consisting of some hundred measures, is significantly reduced by the DCP initialization.
5.2. Comparison of Grid Planning Optimization Methods

Table 5.5: REPL optimization results. N is the number of solutions found (higher is better), M is the mean value of the replaced line length or the time (lower is better). SD is the standard deviation. * indicates comparable results. Other results are not directly comparable due to non-convergence of some solvers (adapted from [124]).

<table>
<thead>
<tr>
<th>solver</th>
<th>solutions found</th>
<th>line length [km]</th>
<th>time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N (%) M (SD)</td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Brigande</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACP*</td>
<td>130 (100.0 %)</td>
<td>8.43 (3.39)</td>
<td>11.7 (12.5)</td>
</tr>
<tr>
<td>SOCWR</td>
<td>13 (10.0 %)</td>
<td>2.93 (2.17)</td>
<td>0.69 (6.11)</td>
</tr>
<tr>
<td>DCP</td>
<td>108 (83.0 %)</td>
<td>7.45 (3.43)</td>
<td>0.43 (3.39)</td>
</tr>
<tr>
<td>ILS</td>
<td>129 (99.2 %)</td>
<td>8.12 (3.95)</td>
<td>1.98 (0.94)</td>
</tr>
<tr>
<td>HYBRID*</td>
<td>130 (100.0 %)</td>
<td>7.75 (3.40)</td>
<td>1.22 (0.45)</td>
</tr>
<tr>
<td>RTS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACP</td>
<td>5 (3.84 %)</td>
<td>18.0 (60.0)</td>
<td>308. (29.0)</td>
</tr>
<tr>
<td>SOCWR</td>
<td>1 (0.76 %)</td>
<td>10.5 (24.1)</td>
<td>43.2 (475.)</td>
</tr>
<tr>
<td>DCP</td>
<td>21 (16.1 %)</td>
<td>93.2 (31.5)</td>
<td>0.24 (0.05)</td>
</tr>
<tr>
<td>ILS</td>
<td>114 (87.6 %)</td>
<td>140. (75.4)</td>
<td>19.0 (12.2)</td>
</tr>
<tr>
<td>HYBRID</td>
<td>118 (90.7 %)</td>
<td>151. (91.5)</td>
<td>19.0 (13.7)</td>
</tr>
<tr>
<td>SB mixed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACP</td>
<td>75 (57.6 %)</td>
<td>20.4 (18.2)</td>
<td>100. (33.5)</td>
</tr>
<tr>
<td>SOCWR*</td>
<td>130 (100.0 %)</td>
<td>32.2 (9.18)</td>
<td>0.90 (1.14)</td>
</tr>
<tr>
<td>DCP*</td>
<td>130 (100.0 %)</td>
<td>33.6 (9.23)</td>
<td>0.22 (0.05)</td>
</tr>
<tr>
<td>ILS*</td>
<td>130 (100.0 %)</td>
<td>30.1 (9.90)</td>
<td>25.4 (11.0)</td>
</tr>
<tr>
<td>HYBRID*</td>
<td>130 (100.0 %)</td>
<td>30.1 (9.85)</td>
<td>6.81 (2.48)</td>
</tr>
<tr>
<td>SB urban</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACP</td>
<td>119 (91.5 %)</td>
<td>22.2 (7.36)</td>
<td>118. (74.7)</td>
</tr>
<tr>
<td>SOCWR</td>
<td>90 (69.2 %)</td>
<td>17.2 (7.29)</td>
<td>3.06 (3.28)</td>
</tr>
<tr>
<td>DCP</td>
<td>115 (88.4 %)</td>
<td>21.2 (7.17)</td>
<td>0.22 (0.07)</td>
</tr>
<tr>
<td>ILS*</td>
<td>130 (100.0 %)</td>
<td>18.5 (6.77)</td>
<td>44.0 (19.9)</td>
</tr>
<tr>
<td>HYBRID*</td>
<td>130 (100.0 %)</td>
<td>18.7 (6.61)</td>
<td>10.2 (6.15)</td>
</tr>
</tbody>
</table>
Table 5.6: Results of the combined optimization. N is the number of solutions found (higher is better), M is the mean line length (lower is better) with the standard deviation SD and the confidence interval CI. (1) = Brigande, (2) = RTS, (3) = SB mixed, (4) = SB urban.

<table>
<thead>
<tr>
<th>solver</th>
<th>solutions found</th>
<th>line length [km]</th>
<th>time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N (%)</td>
<td>M (SD) [CI]</td>
<td>M (SD)</td>
</tr>
<tr>
<td>(1) ILS</td>
<td>130 (100.%)</td>
<td>3.76 (2.86) [0. 10.]</td>
<td>39.7 (26.4)</td>
</tr>
<tr>
<td>Hybrid</td>
<td>130 (100.%)</td>
<td>3.58 (3.05) [0. 14.]</td>
<td>30.1 (19.0)</td>
</tr>
<tr>
<td>(2) ILS</td>
<td>0 (0.0%)</td>
<td>- (-) [- -]</td>
<td>- (-)</td>
</tr>
<tr>
<td>Hybrid</td>
<td>130 (100.%)</td>
<td>0.97 (7.01) [0. 29.]</td>
<td>660. (1757)</td>
</tr>
<tr>
<td>(3) ILS</td>
<td>130 (100.%)</td>
<td>30.1 (9.68) [6. 41.]</td>
<td>314. (125.)</td>
</tr>
<tr>
<td>Hybrid</td>
<td>130 (100.%)</td>
<td>29.9 (9.82) [6. 41.]</td>
<td>78.6 (17.6)</td>
</tr>
<tr>
<td>(4) ILS</td>
<td>130 (100.%)</td>
<td>18.4 (7.35) [0. 35.]</td>
<td>543. (246.)</td>
</tr>
<tr>
<td>Hybrid</td>
<td>130 (100.%)</td>
<td>18.2 (7.17) [0. 35.]</td>
<td>112. (41.2)</td>
</tr>
</tbody>
</table>

5.2.3 Planning Optimization Conclusions

In this section, four metaheuristics, three mathematical programming methods, and the proposed hybrid optimization strategy are compared. Results are shown for four grid planning problems, including switching state optimization, line replacements, the installation of additional lines, and a combined optimization of replacement and switching measures. These problems are benchmarked on four realistic study cases. Both the heuristic approaches and the mathematical programming methods show advantages and disadvantages in this context:

- The ILS finds solutions with the lowest costs of all metaheuristics.
- The linear DCP optimization converges faster than all other methods but does not find valid AC solutions in many runs. Results are similar for the SOCWR method.
5.2. Comparison of Grid Planning Optimization Methods

- The non-convex ACP method often does not converge, or costs of the found solutions are higher than of the other methods with the applied open-source solver.

- The hybrid method is most robust for the analyzed study cases. It finds valid solutions in more than 98% of REPL and IAL runs, and most SSO runs. In the combined optimization, the hybrid method is the only method that finds solutions in all runs.

The results show that the mathematical programming DC model converges in a short time when solved by Gurobi. Another advantage of the mathematical programming methods is the possibility of a combined optimization of generator set points and discrete measures since all methods employ OPF- instead of PF calculations. The non-convex AC problem often diverges and no solution is obtained. Relaxation of the constraints solves this issue but the found solutions are not guaranteed to be optimal and are sometimes infeasible. Another disadvantage is that sophisticated mathematical formulations for each problem are required. These problems can often only be solved efficiently by commercially available solvers.

In comparison, open-source libraries implementing different heuristics are available. A substantial advantage of the greedy (ILS) heuristic is that it converges in most of the IAL and REPL runs. Additionally, the implementation of this heuristic is simpler in comparison to the mathematical formulation of the problem. However, multiple runs with different starting values of the heuristic may be necessary to find better solutions and finding the optimal solution is never guaranteed.

The proposed hybrid method combines the advantages of both methods. Convergence increases and run time decreases by initializing the ILS heuristic with results of the DCP optimization. The hybrid strategy finds solutions in most optimization cases with lower costs and helps to improve the convergence of the ILS heuristic. The hybrid method is applied in the following case studies to determine the grid reinforcement measures.
5.3 Case Studies

In this section, the developed methods introduced in Chapter 4 are applied on two case studies. The following studies are based on real grid data provided by courtesy of the Pfalzwerke Netz AG. The section is divided into three parts. Section 5.3.1 describes the input data of the two case studies. Results of a combined optimization of curtailment and grid planning measures are shown in Section 5.3.2. Section 5.3.3 compares different storage system operational modes and their impact on the amount of curtailed energy per year. Conclusions of the case study are given in Section 5.3.4. A further case study for the SimBench urban HV-grid is shown in Appendix B.

5.3.1 Input Data

The grid model represents a HV grid located in the area of Rhineland-Palatinate, Germany. Real- and reactive power measurements are available in a 15 min resolution at every substation for 2016 and 2017. Figure 5.14 depicts a schematic plot of the HV grid including busbars, substations, power lines, and RES in-feed. The size of each RES marker represents the total generated renewable energy in 2016. Larger markers represent higher maximum in-feed values of the measured periods. Similarly, the size of the load marker represents the consumed energy. Table 5.7 lists the relevant electrical data. The model consists of 24 power lines with a total of 205 km line length. Half of the lines are stubs which directly connect WPPs or underlying MV grids. The other half of the lines are \( N-1 \) relevant and must, therefore, comply with the SCP criterion. The sum of the highest measured power consumption values is 298 MW for 2017. Respectively, 637 MW was measured in terms of generation, which is equal to a factor 2.14 of the peak consumption. The annually consumed/generated energy is rather similar to 675 GWh/612 GWh in 2016 and 650 GWh/816 GWh in 2017. Line replacement measures with a standard type of 2x264-AT1/34-A20SA, a high-temperature conductor, are defined as grid planning measures in consultation with the power system operator. A similar standard type is generally recommended for reinforcements of 110 kV systems by [6]. In the following, maximum line loading limits of 100\% of the maximum current and
voltage limits of 0.9 p.u.-1.1 p.u. must be maintained at all time steps. A following $N$-1 analysis additionally ensures compliance with these limits in case of outages.

Figure 5.14: Electric plot of the HV grid regarded in the case study. The size of each RES and load marker depict the total energy measured at the corresponding substation between 2016-2017.

<table>
<thead>
<tr>
<th>load generation power lines</th>
<th>peak power</th>
<th>annual energy</th>
<th>peak power</th>
<th>annual energy</th>
<th>length</th>
<th>$N$-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>308 MW</td>
<td>675 GWh</td>
<td>568 MW</td>
<td>612 GWh</td>
<td>205 km</td>
<td>12</td>
</tr>
<tr>
<td>2017</td>
<td>298 MW</td>
<td>650 GWh</td>
<td>637 MW</td>
<td>816 GWh</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.3.2 Case Study A – Curtailment vs Reinforcement

In case study A, the proposed framework of this thesis is applied to compare the costs of RES curtailment to the costs of line replacement measures for a plan-
ning horizon of 12 years. The goal is to show how an optimized investment decision can be found and how to determine the trade-off between investment in the infrastructure (CAPEX) and curtailment costs (OPEX) in the time horizon. A sensitivity analysis outlines the variability of results when changing replacements costs, interest rates, depreciation periods, and cost assumptions for curtailment costs.

Assumptions

The proposed time-series-based planning strategy considers operational flexibility and grid planning measures within the same optimization. Several assumptions are needed to compare costs from the operational side, e.g., curtailment within one year and costs of the replacement of power lines. In the following case study, a long-term planning horizon of 12 years is considered. The time series measured in 2016 are the basis of the optimization. In each year, consumption and generation values of 2016 are scaled by a percentage of the previous year. Table 5.8 lists the assumed costs, interest rates, and growth factors for loads and RES. Grid operators have to compensate the owners of RES power plants for the curtailment of energy. Resulting expenditures for the operator are equal to the financial loss of the power plant owner according to federal recommendations [132]. The financial loss is determined by the market premium, which in turn is calculated based on the average market prices of one month (see Section 2.1.2). Since future market prices are per definition unknown, fixed costs are assumed for the curtailed energy per MWh. Costs for the curtailed energy are assumed to be 33 EUR MWh$^{-1}$ resulting from the average values of market prices between 2014-2018 [193]. Power line replacement expenditures are determined with the annuity method as detailed in Section 2.1.2. The annuity method allows to directly compare short-term cash flows from curtailment (OPEX) and the long-term investments for line replacements (CAPEX). It is assumed that infrastructure investments are debt-financed with long-term loans resulting in annuities starting in the year of the investment. In this case study, a depreciation horizon of 50 years, an interest rate of 4%, and replacement costs of 150 000 EUR km$^{-1}$ are assumed as in [194]. The NPVs of all investment paths are determined by discounting the cash flows with the given interest rate and the optimal path is selected based on the NPVs as detailed in Section 2.1.2 and 4.3.1.
Finally, the simulation is performed for additional combinations of costs for the curtailment, interest rates, and costs per kilometer as listed in Table 5.8 as a sensitivity analysis. The variation of the interest rate and the fixed price considers the uncertainty of future market price values as shown in [195].

**Table 5.8**: Case Study A assumptions for load/RES growth, costs, interest rate, and depreciation horizon.

<table>
<thead>
<tr>
<th>growth rates</th>
<th>cost assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>load 1%</td>
<td>RES 5%</td>
</tr>
<tr>
<td>RES 5%</td>
<td>curtailment cost 25-40 EUR MWh(^{-1})</td>
</tr>
<tr>
<td>150 kEUR km(^{-1})</td>
<td>interest 3 – 6%</td>
</tr>
<tr>
<td>40-60 a</td>
<td>depreciation</td>
</tr>
</tbody>
</table>

**Violation Forecast**

First, the overloaded hours per year are compared without applying any grid reinforcement or curtailment measures. Figure 5.15 shows the overloaded hours per year with the assumed growth factors of 5% RES per year and 1% load growth. A total of 2592 h of line overulings are expected for the next 12 years with a maximum of 977 h in year 12, which equals 11.2% of all 8760 hours of the year.

**Figure 5.15**: Overloaded hours per year and line over 12 years.
These line overloading can be mitigated by operational measures, e.g., curtailment of energy or grid reinforcement measures. In the following comparison, four possible solutions are compared:

1. a *worst case* solution considering reinforcement under worst case assumptions and RES reduction factors without time series as a baseline value,

2. a time-series-based *reinforcement only* solution without considering any curtailment,

3. a time-series-based *curtailment only* solution without considering any grid reinforcement measures,

4. a *combined* solution of reinforcement and curtailment measures based on time series as a result of the integrated optimization method developed in this thesis.

**Worst Case Solution**

Calculating grid reinforcement measures based on worst case assumptions is the state-of-the-art method of grid operators. In the following comparison, the *worst case solution* is the baseline value for the time-series-based calculation results. With the worst case method, costs of reinforcement and curtailment are calculated based on fixed worst case scaling factors. Growth factors for load and generation are applied in each year, and power values are scaled with worst case factors (see Section 2.3 for details). Figure 5.16 shows the worst case result for the analyzed HV power system. Each year, the curtailment of generation increases up to a value of $2.9\%$ of the yearly generated energy resulting from the reduction factor of 0.8 for RES in the planning calculation. Result of the curtailment is the NPV of OPEX with €2.39 million in the 12 year horizon assuming fixed curtailment costs of 33 EUR MWh$^{-1}$. Line replacements are necessary starting in year 8 with a total of 125 km being replaced by the 264-AT1/34-A20SA standard type. A NPV of €1.78 million of CAPEX are expected with the annuity method and an interest rate of 4%. The NPV of the TOTEX during the regarded time horizon is €4.18 million.
5.3. Case Studies

Figure 5.16: *Worst case solution* reference values assuming an interest rate of 4%, curtailment costs of 33 EUR MWh$^{-1}$, and a reduction factor of 0.8 for RES curtailment.

**Reinforcement Only Solution**

Figure 5.17 shows the replaced line lengths and resulting annuities per year when only grid reinforcement measures are applied. Line overloads are mitigated by replacing 41.3 km of lines in years 2-3, additional 48.3 km in year 4, and 16.9 km in years 10-11. The resulting NPV of the CAPEX is €4.76 million over the next 12 years with an interest rate of 4%. Considering that the time horizons for HV-grid planning are at least between 3-4 years, the reinforcement only solution is not applicable in practice. It must also be considered that only a few hours of overloads are expected in the first four years and regarding only line replacements is not reasonable from an economic perspective.

**Curtailment Only Solution with OPF**

The second option is to curtail the energy generated by RES for every overloaded hour in the 12 year horizon. This option is not environmentally sustainable and is only calculated to obtain a baseline for the costs of the curtailment. Figure 5.18 shows the curtailed energy in GWh per year and the obtained OPEX in million EUR when assuming a price of 33 EUR MWh$^{-1}$ for the curtailed energy. Up to year 10, the curtailed energy per year is less than 2% of the total generated energy per year.
Figure 5.17: Reinforcement only solution assuming an interest rate of 4%, depreciation horizon of 50 years, and 150 kEUR km\(^{-1}\) replaced line.

Between year 9-12, more than 20.4 GWh-32.7 GWh have to be curtailed to mitigate line overloading. This amount of energy equals more than 2–3% of the annually generated energy. The cash flows of the OPEX range between nearly zero in the first 3 years up to a value of more than €1.08 million in year 12. A NPV of the TOTEX of €2.80 million is obtained for the 12 year horizon.

Figure 5.18: Curtailment only solution assuming a growth rate of 5% of RES per year and expenditures of 33 EUR MWh\(^{-1}\) for the curtailed energy.
Combined Solution

Figure 5.19 shows the results of a combined optimization of grid reinforcement measures and curtailment of RES with the time-series-based method developed in this thesis. The interest rate for the line replacement measures is 4% and a price of 33 EUR MWh$^{-1}$ for the curtailment of energy is assumed. Up to year 7, no reinforcement measures are reasonable from an economic point of view. Line over-loadings are mitigated by curtailing a total of 22.0 GWh of energy resulting in a NPV of €0.55 million of OPEX for the curtailment. In year 8, 42 km of lines are replaced resulting in an annuity of €0.30 million per year and a NPV of CAPEX of €1.0 million. The NPV of TOTEX of the 12 year horizon is €1.56 million.

**Figure 5.19:** Combined solution of reinforcement and curtailment measures assuming an interest rate of 4%, depreciation horizon of 50 years, 150 kEUR km$^{-1}$ replaced line, and 33 EUR MWh$^{-1}$ curtailment expenditures.

Comparison

Figure 5.20 (a) compares the NPVs of cash flows of the regarded 12-year investment period. Results are shown for the worst case, the reinforcement only, the curtailment only, and the combined optimization solutions. The second highest total NPV of €4.17 million is expected when applying the worst case method. An
increase of 14.0% in expenditures with a NPV of €4.76 million is obtained by applying only reinforcement measures without considering any curtailment. The main reason for the high expenditures of the reinforcement only solution are unreasonably high investments in the first years to mitigate only a few hours of line overloads. Only a low amount of curtailment is needed to solve the line loading problems up to year four as shown by the curtailment only and the combined solution. A NPV of OPEX of €2.8 million is expected when considering only curtailment measures. The major part of the expenditures is expected for the final four years. Even though it is not a environmentally sustainable solution, the curtailment of the energy results in 67% of the expenditures in comparison to the worst case solution in the 12-year planning horizon. The combined optimization of reinforcement and curtailment measures yields the lowest overall expenditures with a NPV of €1.56 million. The NPV of the total cash flows is less than 38% of the worst case solution result.

Figure 5.20(b) shows the DCFs of the final year only. It can be assumed, with a further increase of RES in the power system, that the expenditures will increase in the subsequent years and that a comparison of the last year is highly relevant for the investment decision. Power system operators should, therefore, consider the NPV and the DCFs of the final year when deciding whether to invest or not. The DCF in year 12 of the worst case result are highest with a total of €0.68 million. Expenditures of the replacement only and curtailment only are similar with €0.44 million and €0.46 million respectively. The combined approach has significantly lower expenditures with €0.20 million, which equals less than 30.0% of the worst case result. The comparison of the DCF of year 12 shows that applying only curtailment measures leads to higher TOTEX than applying only reinforcement measures when regarding later periods. Even though the sole application of curtailment measures yields a lower NPV in the 12-year period, it is more costly than the investment in the infrastructure in the long run.

Both comparisons show that a time-series-based planning method allows to significantly reduce expenditures in planning by calculating the amount of curtailed energy in each year more accurately than with the worst case method. The proposed time-series-based method helps to integrate RES more sustainably than the worst case approach since the power system operator can determine curtailment measures in detail and to plan the power system accordingly.
5.3. Case Studies

Figure 5.20: (a) Comparison of the NPVs of the total cash flows for the worst case, reinforcement only, curtailment only, and the combined solution based on time series. (b) Comparison of the DCF of year 12 only.

Cost Sensitivity Analysis

The obtained results of the combined optimization depend on the assumed input parameters. A high interest rate for line replacement measures postpones these measures to later years. If curtailment costs are assumed to be high, reinforcement measures are considered earlier in the planning horizon. Figure 5.21 shows three examples of varied interest rates and curtailment costs. With a moderate and high interest rate of 4 and 5% respectively, line replacement measures are recommended starting in year 9 (compare Fig. 5.21 (a) and (c)). A low-interest rate of 2% reduces the amount of curtailed energy in year 5-8. Instead, line replacement measures are recommended starting in year 5 as shown in Fig. 5.21 (b).

Figure 5.22 shows a detailed sensitivity analysis on the TOTEX for the parameters: curtailment cost, depreciation horizon, interest rate, and line cost per km. Each parameter is varied between $-90\%$ and $100\%$ of its initial value while fixing the remaining parameters to their original value. A steeper gradient of the resulting curve equals a high sensitivity to the parameter. Increasing the depreciation horizon further from 50 years has the lowest effect on the NPV of the TOTEX. A decreasing depreciation horizon, however, increases the TOTEX significantly. Reducing the curtailment costs and the costs for each replaced km of power lines has a similar effect on the TOTEX, where an increasing interest rate of more than $5\%$ shows a more shallow gradient. Decreasing the costs per km as well as the curtailment costs would lead to a sharp reduction in the expenditures. A lesser gradient is obtained for a decreasing interest rate. The results show that the most crucial cost
factors are the assumed cost of the curtailed energy, the interest rate, and the cost per km for each replaced line. The extreme values, such as a short depreciation horizon and low costs per kilometer, are not realistic and should illustrate the sensitivity to the parameter.

Figure 5.21: Comparison of three different interest rates and curtailment cost assumptions.

Figure 5.22: Sensitivity analysis. Each parameter is varied between $-90\%$ to $200\%$ of the initial values at $0\%$ variation.
$N$-1 Analysis

HV systems must fulfill the SCP criterion, and critical system states must be avoided. A critical state is defined as a situation in which the loading limit of one power line is exceeded if another power line is not in service. No line outage is allowed to lead to a disconnection of supplied loads. $N$-1 situations can be mitigated by different operational measures, including the curtailment of RES in times of high in-feed or a change in the switching state. Figure 5.23 shows the $N$-1 analysis result for each year considering the reinforcement measures for the HV grid. Between 1500-2600 hours in each year are critical when the normal switching state is applied and RES are not curtailed. In these hours, the outages of lines 13-15 and line 17 can lead to over loadings of parallel lines if no operational measure is taken. The developed planning method automatically tries to solve the critical $N$-1 states by applying curtailment measures and changes in switching states. In more than 63% of all time steps, line outages can be mitigated by curtailing the energy generated by the RES when one of the parallel lines 13 or 14 fails. 98.0 – 99.6% of line over loadings are solved by curtailment in case of an outage of line 15 and 77.2 – 86.0% when line 17 fails. High loading situations with low generation from RES are the reason for the remaining time steps. During these time steps, a change of the switching state can mitigate the critical $N$-1 situations.

![Figure 5.23](image)

**Figure 5.23**: Relevant $N$-1 line outages in each year and how these are solved by switching measures or the RES curtailment.
Calculation Time Comparison

A total of $2^{(Y+1)}$ year simulations are needed to obtain the optimal investment path for $Y$ years as detailed in Section 4.3.1. Therefore, $35040 \cdot 2^{(Y+1)}$ PF calculations are necessary to get the full decision tree for time series in 15 min resolution. For case study A, more than 287 million PF simulations are required, not counting the $N-1$ analysis. Fast implementations and methods are, therefore, essential. In this case study, the methods introduced in Chapter 4 were applied. Furthermore, the fast parallel power flow solver of [196] was used to calculate the time series results. Additionally, the total amount of power flow calculations can be reduced significantly by separating the decision tree into several smaller periods, as explained in Appendix B. By cutting the tree into the three periods, the number of PF calculations is reduced to 3.3 million. Figure 5.24 shows a comparison of the calculation time for the full simulation vs the calculation in three periods of four years. The timings are measured on a modern desktop computer. To calculate the full tree, 311 min are measured for the time series simulation, 61 min to determine the operational measures, and 132 min to determine the reinforcement measures resulting in a total calculation time of 504 min. This time is reduced to 5 min by cutting the tree into 3 periods. The reduced tree, however, cannot guarantee to find the optimal solution for the whole period of 12 years.

![Figure 5.24](image)

Figure 5.24: Timings of $2^{13}$ year simulations with 287 million PF calculations vs 96 year simulations with 3.3 million PF calculations (see Appendix B for details).
5.3.3 Case Study B – Storage System Operational Modes

An increasing share of storage systems in the power system is expected in the next 10 to 20 years as motivated in Section 1.1. These storage systems can lead to an increase of grid congestions or reduce overloading depending on their mode of operation. An own-consumption oriented operation balances load and generation, while a market-optimized operation may lead to an increase in line loadings. These operational modes can be simulated with the developed storage model in Section 4.3.2. In this case study, two exemplary storage operation modes, resulting from the modelling approach, are compared:

1. an own-consumption optimized storage system operational mode where the storage systems balance load and generation within a virtual power plant (VPP), and

2. a market-optimized storage system operation where the charge- and discharge cycles are optimized according to a market-price signal.

It is assumed that the storage system owner is a separated entity from the power system operator. The power system operator has, therefore, no direct control of the storage system and CAPEX for the installation costs of storage systems are not considered in the following case study. Instead, the power system operator instructs the VPP owner to reduce in-feed to mitigate line loading and bus voltage violations. Depending on the state of charge, the VPP owner then either reduce the storage system output or curtailment measures at the corresponding bus. This flexibility usage leads to OPEX for the power system operator. It is assumed that the cost of the flexibility usage is similar to the cost of curtailment. This case study addresses the following questions:

- What is the impact of the two storage system operational modes on line loadings and bus voltages?
- Is the amount of curtailed energy reduced when storage systems are installed in comparison to Case Study A?
• Which implications result for power system planning due to the increase of storage systems?

Assumptions

Figure 5.25 shows the assumed storage configuration for the following case study. Two areas are defined based on the existing feeders. In each area, generation, load, and storage systems are optimized within one VPP. It is assumed that the VPP controls the storage systems in its area, the RES, and covers the consumption in the area. The VPP either optimizes the storage system according to a market price signal or tries to balance load and generation in that area to optimize own-consumption of the VPP.

![VPP configuration](image)

**Figure 5.25:** VPP configuration. The storage system schedules in feeders 1 and 2 are optimized based on load and RES generator of these feeders.

In each year, an increasing amount of installed storage capacity is assumed. Figure 5.26 shows the total power of the storage systems in MW as well as the share of storage capacity to the peak load and peak consumption. In the first year of the planning horizon, 7.12 MW of storage power is installed in the grid, which equals 1% of RES peak generation and 2% of peak load. The amount of storage system power rises to 71.1 MW in year 12, which is 6.5% of RES power and 18% of peak
load. The storage capacity is assumed to be four times the storage power, which is an average value of battery technologies according to [7]. The installed energy equals 28.48 MWh in the first year and 285 MWh in year 12. Table 5.9 lists additional cost assumptions similar to Case Study A.

Figure 5.26: Increasing installed storage power per year in MW (left). Relative share of storage power on peak generation and load (right). The relative share of peak load is higher since the load increase of 1% per year is smaller than the RES with 5% per year.

<table>
<thead>
<tr>
<th>growth rates</th>
<th>cost assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>load</td>
<td>RES</td>
</tr>
<tr>
<td>1%</td>
<td>5%</td>
</tr>
<tr>
<td>storage</td>
<td>curtailment cost</td>
</tr>
<tr>
<td></td>
<td>150 kEUR km⁻¹</td>
</tr>
<tr>
<td></td>
<td>4 %</td>
</tr>
</tbody>
</table>

Table 5.9: Growth rates and cost assumptions in Case Study B.

Storage System Output

Different time series for the storage systems result depending on the optimization strategy of the VPP. Figure 5.27 shows an exemplary comparison of the own-consumption optimized storage system operation versus the market-optimized storage system operation. The own-consumption optimized operation in Fig. 5.27 (a) reduces the residual load curve in times of high generation by charging the storage systems with maximum power (time steps 0-22). In times of lower generation,
the storage systems discharge to cover loads and to free charging capacity for times of higher generation (time steps 22-26). Such a storage system behaviour reduces the mean line loadings leading to lower amounts of necessary curtailment or a reduction of necessary line replacement measures. The charging and discharging cycles vary when using market price values as incentives for the storage systems. Figure 5.27 (b) shows the varying cycles resulting from the market prices. Here, no systematic reduction of the residual curve can be seen. The VPP tries to optimize revenues by charging the storage system in times of lower prices and discharging in times of higher prices. The resulting charging and discharging cycles can reduce or increase the line loadings as visible between the time steps 10-20.

**Figure 5.27:** Exemplary storage system output depending on the storage model. The residual curve of generation and load is either a) flattened by the storage systems or b) changes according to the market price signal.

### Results

Figure 5.28 shows the results of the 12-year planning horizon, including the curtailed energy, the total replaced kilometers of power lines, and the NPV of TOTEX for the two storage operational modes. The result from Case Study A without in-
stalled storage systems is shown as a baseline scenario. Both storage systems operational modes result in the same necessary replaced kilometer of power lines of 42 km. The availability of storage systems in VPP 1 reduces the line loadings in several time steps, which in turn allows postpone the replacement of these power lines by one year. A later replacement of these power lines results in a lower NPV of CAPEX for both storage operational modes. However, the storage system schedules have to be changed by the VPP. During times of high line loadings, (16.8 GWh) of the storage system schedules must be varied by the VPP owner in the case of market-optimized storage behaviour. It is assumed that the cost for this storage system schedule variation is equal to the cost for the curtailed energy resulting in higher OPEX. In comparison, the amount of shifted energy is less when the storage systems are optimized for own-consumption. An amount of 6.3 GWh must be shifted in this case. For the market-optimized storage result, the NPV of TOTEX increases by 6% from €1.56 million to €1.64 million. A reduction of 4% to €1.49 million in TOTEX is obtained when the storage systems are operated in an own-consumption optimized manner.

The NPV of TOTEX varies depending on the storage system operational mode. A reduction is possible due to the balancing of loads and RES generation at the same buses in the case of the own-consumption optimized schedules. In the case of the market-optimized operation, the storage system schedules depend on the

![Figure 5.28: Optimization result without storage systems and with the two storage system operational modes.](image-url)
market-price time series of the given year (2016). An increase of line loadings is the result since a high in-feed of RES and high market prices are possible in this grid area leading to an in-feed of storage systems and RES at the same time. In a different year, the local in-feed of RES may be high in times of lower market prices. In this case, the storage system outputs would lead to lower outputs and thus reduce congestions. The power system operator should, therefore, design the system for worst case of a maximum power output of the storage system. Alternatively, a guaranteed provision of flexibility by the storage operator is an alternative option. A simulation of this provision requires to model a contract model or a local flexibility market to procure storage flexibility and is not targeted in this thesis.

5.3.4 Case Study Conclusions

The two case studies show two exemplary applications of the presented time-series-based power system planning strategy. This summary draws several conclusions from the case studies and gives an outlook on further possible improvements.

Case Study A - Curtailment vs Reinforcement

Case study A shows the advantages of the developed planning method which optimizes operational flexibility from RES curtailment and conventional planning measures. The combined consideration of curtailment measures and line replacements reduces the NPV of TOTEX by more than 60% to €1.56 million in comparison to the baseline value from the worst case method of €4.17 million. An increase of 14% of the TOTEX as with the worst case method are expected when using only conventional replacement measures. When applying only curtailment measures, without any line replacements, the annual curtailment exceeds the 3% limit. However, expenditures can be reduced by 32% in comparison to the baseline. Curtailing the energy from RES for the next 12 years is, naturally, no acceptable solution according to law. The resulting expenditures vary according to the assumed costs. A cost sensitivity shows the impact on the cost assumptions on the results. The highest impact on the TOTEX has the interest rate, the line cost per km, and the assumed
costs for each MWh of the curtailed energy. Furthermore, an $N$-1 analysis shows that the obtained replacement measures ensure a secure power system operation. All outage situations can be solved by the curtailment of RES or changing the switching state. Finally, a calculation time comparisons show the applicability in practice.

**Case Study B - Storage System Operational Modes**

Case study B analyzes storage system operational modes and shows the impact of an own-consumption optimized storage behaviour vs a market-optimized strategy with two VPPs. Results show that own-consumption oriented operational mode has a balancing effect on the line loadings allowing to postpone line replacements in the planning horizon. The market-optimized operation, however, may lead to additional overloading in times of high already loadings due to RES in-feed. The critical situations can be mitigated by the controlling storage systems and the curtailment of energy. The NPV of the TOTEX increases by 6% in comparison to Case Study A when storage systems are operated in a market-optimized way. In comparison, the NPV is reduced by 4% when storage systems are optimized for own-consumption.

**Outlook**

Several assumptions are necessary to conduct the studies as shown in this section. First, the curtailed energy is calculated with an OPF-based model. The OPF strategy reduces the amount of the curtailed energy to a minimum leading to a lower amount of curtailed energy than expected in live operation. Renewable power plants are often controlled in discrete steps of 60%, 30%, and 0% of the maximum output in lower voltage levels, which would increase the curtailed energy and thus the resulting costs. Implementing discrete steps results in a mixed-integer problem, which is harder to solve. Second, the input time series are obtained from measurements and scaled according to the expected load and generation growth. A generation of synthetic future time series could decrease the uncertainty of the obtained results.
All storage systems in study B are assumed to be batteries with very high efficiency. A variation of the storage parameters or a definition of other types, e.g., power-to-gas installations, increases the variability of the results. The market prices for the marked-optimized storage operation are from 2016 and fit the scaled time series from 2016. Future market prices are, similar to the future generation and load time series, unknown and could be simulated as well. Furthermore, the simulation a local flexibility market to procure storage flexibility could be integrated in the simulation.
6 Conclusions

6.1 Summary and Contributions

Innovative planning strategies allow to fully integrate operational flexibility, provided by RES, flexible loads, and storage systems, into the planning process of power systems. Grid operators are able to reduce investments by considering fluctuating generation, operational flexibility, and conventional grid planning measures. Different requirements are to be considered when developing new planning strategies depending on the voltage level and topology. The HV level must be particularly reliable, which requires considering the $N$-1 criterion in planning. Additionally, the meshed infrastructure differs from lower voltage topologies. In this thesis, a power system planning strategy for meshed HV sub-transmission systems is developed, which integrates the optimization of operational flexibility and conventional grid planning measures based on time series simulations. The majority of developments of this thesis are integrated into the open-source power system planning tool pandapower. This thesis’s main contribution is the developed multi-year planning strategy implemented in Chapter 4. Results showing the possibilities of the strategy and the validation of the contributed methods are outlined in Chapter 5.

Contributions

Chapter 4 details the implementation of the developed planning framework. A multi-year planning strategy is developed considering operational flexibility models and conventional grid planning measures in a combined optimization. This strategy enables grid planners to find an optimized investment decision in the power system infrastructure. With the developed methods, it is possible to find
a trade-off between the costs of operational measures and grid planning measures.

- The contribution of Section 4.2 is the developed time series module, which is integrated into the open source software pandapower. The time series module allows simulating multiple years in a short time while considering operational flexibility. The available pandapower controllers are integrated into the module, allowing to model tap-changer, RES controller, and storage systems.

- Simulating the operational side in the planning stage increases calculation time and complexity. Therefore, several improvements to reduce the calculation time are developed in Section 4.2.2. The first contribution of this section is the tailored NR implementation. This implementation reduces the PF calculation time by efficiently creating the Jacobian and admittance matrix directly in a compressed storage format. The second contribution is the reduction of the conversion overhead between two time steps when simulating time series with pandapower. The time series module automatically reduces calculation overhead by storing several matrices in memory.

- A further contribution to reduce calculation time is the ML method to predict time series calculation results explained in Section 4.2.3. With regression and classification techniques, relevant time steps for grid planning are rapidly identified. The simulation of multiple years and $N$-1 situations is possible with this approximation method.

- Furthermore, this thesis contributes a multi-year optimization strategy in Section 4.3. With this strategy, multiple consecutive years can be analyzed to find an investment decision, including operational and conventional planning measures. In each year, operational flexibility and conventional measures are regarded, resulting in a tree-structure for multiple years. In the final year of the planning horizon, the minimum NPV for each branch are compared, and the optimal investment path is obtained.

- This combined optimization of operational flexibility and grid planning measures requires implementing operational flexibility models and grid planning algorithms. Section 4.3.2 contributes additional pandapower simulation models representing two RES curtailment methods. One of the curtailment meth-
ods is based on OPF calculations, while the other calculates static curtailment factors. Furthermore, two storage system models are implemented to simulate either market-optimized or own-consumption optimized storage systems behaviors and VPPs.

- Grid planning requires to optimize the power system by deciding which power line to reinforce or which additional power line to be built. The formulation of this requirement results in a discrete, non-convex optimization problem, which can be solved by different strategies, including metaheuristic and mathematical programming optimization methods. The contribution of Section 4.3.3 is a hybrid optimization method, which combines the advantages of heuristics and mathematical optimization. Furthermore, several heuristics are implemented to solve the planning task, including GA, FWA, and GWO. Additionally, mathematical programming methods are integrated to solve the network expansion problem with AC-, DC-, and quadratic optimization models.

Summary of Results

Chapter 5 validates the developed methods on four open-source benchmark systems and applies the planning strategy on a real power system model in two case studies.

- Section 5.1.1 shows results of the time series simulation methods. A reduction of up to 83% of the total calculation time is possible with the implemented time series module. The improved NR implementation provides further calculation time reductions. The developed method is up to 30 times faster than comparable open-source implementations written in Python. Nevertheless, exhaustive time series analysis of multiple years and $N-1$ cases require even shorter simulation times.

- The implemented ML concepts solve this issue. Several regression and classification methods are compared in Section 5.1.2. Results show that a trained ANN can accurately predict bus voltage magnitudes and power line loadings in milliseconds. The ANN correctly identifies over 99.4% of the critical time steps for the benchmark cases. For these cases, the training time for the
ANN is about 10% of the overall calculation time. The majority of time is spent generating the training data.

• Section 5.2 compares four grid planning metaheuristics and three mathematical programming models. An exhaustive comparison of these methods identified the ILS as the best metaheuristic in terms of run time and low solution costs. The ILS is combined with the linear DC optimization model as a hybrid optimization strategy. Results show that the hybrid strategy is able to find lower-cost solutions in shorter run times than the existing methods for the benchmark cases. The hybrid method is the only method that converges in all benchmark cases when regarding a large optimization space, including replacement and switching measures simultaneously. Additionally, the run time is reduced by 75%-80% in comparison to the existing ILS heuristic.

• Section 5.3 applies the developed framework in two case studies. Results are shown for a real HV power system model. In Case Study A, a combined optimization of operational flexibility from curtailment measures and power line replacements is regarded. In this study, the developed OPF curtailment model is applied. Results show that a cost reduction of more than 60% in comparison to traditional worst case methods is possible when using a combined optimization of curtailment measures and conventional planning measures. The validity of the results is shown further by a sensitivity analysis of the assumed cost parameters. Case Study B shows the impact of different storage system control strategies on the planning result. An own-consumption optimized storage system operation further allows to reduce curtailment measures and postpone line replacements. A market-optimized storage system optimization can lead to an increase in expenditures for the power system operation, depending on the market price signal.

6.2 Outlook

The presented multi-year power system planning method allows to find investment decisions for meshed HV power systems. The framework consists of a time series simulation part and the combined optimization strategy for operational flexibility
and conventional measures. Several aspects should be further researched and improved regarding both parts.

**Time Series Calculation**

Conducting a study case as in Section 5.3 requires several assumptions. In this thesis, scaling factors are applied to the input time series measured in previous years. Scaling the existing time series accounts for the increase of load and generation for future years. A sophisticated generation of time series for future years and scenarios could further improve the study results [197, 198]. Similar assumptions are necessary for future market prices, which are per definition unknown. However, it can be assumed that market participants can be modelled more accurately by integrating more measurements in the smart grid, allowing to improve market-price forecasts [199].

The implemented time series module allows calculating results of multiple years in a short time when several matrices are constant. Updates to the admittance matrix by changing the tap-changer position or the switching states require recalculating the matrix. This issue could be solved by partially updating the matrix and further reduce calculation time. Further improvements are possible by implementing the power flow solver in a low-level programming language. A promising solution is to perform $N$-1 security analysis in parallel on GPUs as proposed by [196, 200, 201].

The presented approximation methods based on a ANN can further be enhanced by improving the training data. Exemplary results with training data generated by the scenario generator from [157] indicate that prediction results improve with more diverse training sets. Additionally, hyperparameters could be optimized automatically for each specific power system with [165], and new architectures could be tested. The method can further be extended by incorporating additional information in the input data, such as switching state or tap-changer positions. Such an extended input dataset, however, requires more training data and thus more computational power.
Optimization

Several additional operational models of the pandapower control module are compatible with the implemented framework. Additional operational strategies could be integrated further with this module, including demand-side-management strategies or coupling to the heat sector. For example, the open source pandapipes software could be coupled to the framework to integrate gas and heat pipe systems [202].

Additional storage system models could be implemented representing, for example, a fleet of electric cars. These are rather consumers from a DSO perspective and not accessible by the DSO as flexibility. The developed curtailment strategy uses OPF calculations or static factors to determine curtailed energy. Different curtailment strategies could be integrated depending on the operational restrictions of the specific distribution system. For example, curtailment in discrete steps is common for RES with a low output power in Germany, leading to additional curtailed energy [203].

The developed hybrid method is based on the ILS metaheuristic and a DC power model. This hybrid approach could further be improved by using other cost functions or custom mutation operators for the GA. Additionally, the hybrid method’s mathematical programming initialization strategy could be enhanced by using commercial solvers or testing new mathematical models of [54].

Further Applications

The developed methods are integrated into a graphical user interface within the project SpinAI. With this integration, a user-friendly application for German HV grid operators is possible. Furthermore, international applicability in sub-transmission systems is a potential extension by adapting the cost assumptions according to the corresponding countries’ regulations. Additionally, the method can be applied to different voltage levels by integrating several expansions to the optimization and simulation strategy. Since MV and LV power systems rarely operated as meshed systems, a radiality or open-loop constraint must be added for the application in these systems. Regarding the EHV level, a distributed slack implementation could
help to obtain more realistic results, and an extended model of EHV grid equivalents is required. Finally, the method could be expanded by integrating HVDC power line models for the planning of EHV systems.
Appendix

The appendix is divided into three sections describing further methods, implementations, and results. Appendix A explains additional ML models and the CRS format. Appendix B details the improved NR implementation from Section 4.2.2 and the multi-year period planning approach. Finally, Appendix C shows further results regarding the optimization heuristics as well as a case study for the SimBench HV urban grid.

A - Further Methods

k-Nearest Neighbors

k-Nearest Neighbors (k-NN) is a non-parametric learning algorithm. Contrary to other learning algorithms, training data is not discarded after the model is built. Instead, k-NN keeps all training examples in memory. The category of a new example is predicted by measuring the distance to \( k \) of its neighbors and returning the majority label (classification) or the average label (regression). For this, distance functions are used. Frequently used functions in practice are the Euclidean distance or cosine similarity [159]. Since the k-NN algorithm keeps all examples in memory, prediction times can be very long for large data sets. Figure B.1 shows an example of the method.

Compressed Row Storage Format

Buses in realistic power system models are connected to only a few other buses. Thus, the admittance matrix \( Y \) and the Jacobian matrix \( J \) have a high sparsity and
Appendix

Figure B.1: k-NN classification example. The training data is used to obtain categories by measuring the distance between \( k \) data points. In this example the number of neighbors is \( k = 5 \) and two categories of labels are defined.

can be stored in the compressed row storage (CRS) format. In CRS format, subsequent nonzero elements of a matrix \( A = (a_{ij}) \in \mathbb{R}^{n \times n} \) are stored in contiguous memory locations. Instead of storing every entry of the matrix, three vectors are stored. These vectors contain the positions and values of the nonzero elements. The first vector, the data data vector, \( A_x \) stores the nonzero values of \( A \). A value at position \( k \) in the array is accessed by an index operator [:]

\[
a_{ij} = A_x[k] \quad \text{(B.1)}
\]

The vector \( A_j \) contains the column indices of the entries in \( A_x \) as integers:

\[
A_j[k] = j \quad \text{(B.2)}
\]

The row pointer vector \( A_p \) contains integers, which store the locations in \( A_x \) that start a row:

\[
A_p[i] \leq k < A_p[i + 1] \quad \text{(B.3)}
\]

It is defined that \( A_p(n + 1) = \text{nnz} + 1 \), where \( \text{NNZ} \) is the number of nonzeros in \( A \).

Instead of storing \( n^2 \) elements, only \( 2\text{nnz} + n + 1 \) values need to be stored. This means that the higher the sparsity of \( A \), the lower is the required memory to store \( A \) [204].
B - Further Implementations

Pseudocode of Section 4.2.2

The following pseudocodes in Listings B.1-B.2 calculate the partial voltage derivatives as explained in Section 4.2.2. The listings are adapted from [117].

**Listing B.1: Calculation of derivatives 1**

```plaintext
for i in rows of Y:
    for k in nonzero elements per row:
        I[i] = I[i] + Y_x[ik] · V[k]
        ∂V_{m,x}[ik] = Y_x[ik] · V_{norm}[k]
        ∂V_{a,x}[ik] = Y_x[ik] · V[k]
    end
    temp[i] = I[i] · V_{norm}[i]
end
```

**Listing B.2: Calculation of derivatives 2**

```plaintext
for i in rows of Y:
    for k in nonzero elements per row:
        ∂V_{m,x}[ik] = ∂V_{m,x}[ik] · V[i]

        if diagonal element:
            ∂V_{m,x}[ik] = ∂V_{m,x}[ik] + temp[i]
            ∂V_{a,x}[ik] = I[i] - ∂V_{a,x}[ik]
        end

        ∂V_{a,x}[ik] = ∂V_{a,x}[ik] · jV[i]
end
end
```

Creation of the sub-matrices $J_{11}$ and $J_{12}$ of the Jacobian matrix $J$ is listed in Listing B.3. The entries of $J_{21}$ and $J_{22}$ are written to $J_x$, $J_p$ and $J_i$ in a similar way. An additional iteration over the number of rows ($N_{pq}$) and the corresponding nonzero elements in $\partial V_m$ and $\partial V_a$ of these rows is required for this.
Listing B.3: Creation of CRS vectors for $J_{11}$ and $J_{12}$

```python
nnz = 0
for row in 0 to length(pvpq):
    nnz_row = nnz
    bus = pvpq[row]
    for k in $Y_p[bus]$ to $Y_p[bus+1]$:
        j = $bus_{indices}[Y_i[k]]$
        if pvpq[j] == $Y_i[k]$
            # entry for $J_{11}$
            $J_x[nnz] = \partial V_{a,x}[k].real$
            $J_i[nnz] = j$
            nnz += 1
        if j >= $N_{pv}$:
            # entry for $J_{12}$
            $J_x[nnz] = \partial V_{m,x}[k].real$
            $J_i[nnz] = j + N_{pv}$
            nnz += 1
    end
    end
    $J_p[row+1] = nnz - nnz_row + J_p[row]$
end
```

Multi-Year Simulation in Periods

The multi-year planning method requires to calculate $2^{(Y+1)}$ year simulations to obtain the optimal investment path. For a time series resolution of 15 min, $35040 \cdot 2^{(Y+1)}$ PF calculations are necessary to get the full decision tree as described in Section 4.3.1. The number of power flow calculations can be reduced significantly by separating the decision tree into several smaller periods. Figure B.2 depicts this concept of cutting the decision tree into smaller periods. After a period of 3 years, the tree is cut by determining the lowest NPV of period 1. The solution of the node with the lowest NPV is the initial solution for the following periods. In this example,
the number of power flow calculations is reduced from 35.9 million to 0.56 million calculations. By cutting the tree into smaller periods, however, it is not guaranteed that the optimal investment path is found.

Figure B.2: Multi-year simulation in periods.

C - Further Results

Heuristic Optimization

The time spent by evaluation type for each metaheuristic is shown in Fig. B.3. Each method either evaluates topology restrictions (connected buses), technical restrictions (line loading and voltage evaluation) or costs. HC and ILS perform mainly power flow and cost evaluations since only one measure is applied at a time. If a valid topology is found, buses are rarely disconnected in comparison to the mutation strategies of the remaining heuristics.

SimBench Curtailment Study

In this section, the proposed framework is applied to the SimBench urban HV-system as an addition to the case studies shown in Chapter 5. The case studies compares the costs of RES curtailment to the costs of line replacement
Figure B.3: Percentage of time spent within an optimization level. Topology violations result from invalid switching states, PFs evaluate line loading and voltage limits, cost evaluations determine costs when no constraints are violated (taken from [125]).

measures for a planning horizon of 10 years. The grid data and the corresponding time series are obtained from [185]. Further details and results of this case study are published in [121].

Assumptions

In the following case study, a long-term planning horizon of 10 years is considered. The time series provided with the SB urban power system are the basis of the optimization. In each year, consumption and generation values of are scaled by a percentage of the previous year. Table B.1 lists the assumed costs, interest rates, and growth factors for loads and RES. Similar to case study A, fixed costs are assumed for the curtailed energy of 33 EUR MWh$^{-1}$ and a depreciation of 50 years with an interest rate of 4%, and replacement costs of 150 000 EUR km$^{-1}$ are assumed for power line replacements. As conventional measures, power lines replacements with the half the installed impedance are assumed. The NPVs of all investment paths are determined by discounting the cash flows with the given interest rate and the optimal path is selected based on the NPVs similar to case study A in Section 3.1.1.
Table B.1: SimBench Case study assumptions for load/RES growth, costs, interest rate, and depreciation [121].

<table>
<thead>
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<th>cost assumptions</th>
</tr>
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<tr>
<td>load</td>
<td>RES</td>
</tr>
<tr>
<td>1%</td>
<td>5%</td>
</tr>
<tr>
<td>curtailment</td>
<td>cost</td>
</tr>
<tr>
<td>cost line</td>
<td>interest</td>
</tr>
<tr>
<td>33 EUR MWh⁻¹</td>
<td>150 kEUR km⁻¹</td>
</tr>
<tr>
<td>4%</td>
<td>50 a</td>
</tr>
</tbody>
</table>

Violation Forecast

Figure B.4 shows the overloaded hours per year with the assumed growth factors of 5\% RES per year and 1\% load growth. A total of 3672 h of line overloads are expected for the next 10 years with a maximum of 908 h in year 10, which equals 10.4\% of all 8760 hours of the year. The line overloading results from the high in-feed of RES.

Worst Case Solution

Costs of reinforcement and curtailment are calculated based on fixed worst case scaling factors with the worst case method. Figure B.5 shows the worst case result for the SB urban case. Each year, the curtailment of generation increases up to a value of 2.0\% of the yearly generated energy resulting from the reduction factor of 0.8 for RES. Result of the curtailment is the NPV of OPEX with €2.71 million in the 10 year horizon assuming fixed curtailment costs of 33 EUR MWh⁻¹. Line replacements are necessary in year 10 with a total of 13.8 km being replaced by a parallel line with the same standard type. A NPV of €0.07 million of CAPEX are expected with the annuity method and an interest rate of 4\%. The NPV of the TOTEX during the regarded time horizon is €2.77 million.

Reinforcement Only Solution

Figure B.6 shows the replaced line lengths and resulting annuities per year when only grid reinforcement measures are applied. Line overloads are mitigated by replacing 13.8 km of lines in year 3. The resulting NPV of the CAPEX is €0.6 million over the next 10 years with an interest rate of 4\%. 
Figure B.4: SimBench Case Study - forecast of power line loading violations [121].

Figure B.5: SimBench Case Study - worst case solution assuming an interest rate of 4\%, depreciation of 50 years, 150 kEUR km\(^{-1}\) replaced line, and 33 EUR MWh\(^{-1}\) curtailment expenditures [121].

Curtailment Only Solution with OPF

Figure B.7 shows the *curtailment only* solution without considering any conventional measures in the 10 year horizon for the SB power system. The curtailed energy is shown in GWh per year as well as relative to the absolute generation an that year. The obtained OPEX are depicted in million EUR when assuming a price of 33 EUR MWh\(^{-1}\) for the curtailed energy. Up to year 10, the curtailed energy per year is less than 2\% of the total generated energy per year. A total of 155 GWh of energy is curtailed in the 10 year horizon. The cash flows of the OPEX range between zero in the first 3 years up to a value of more than € 1.46 million in year 10. A NPV of the
TOTEX of €3.69 million is obtained for the 10 year horizon.

**Figure B.6:** SimBench Case Study - reinforcement only solution assuming an interest rate of 4%, depreciation of 50 years, and 150 kEUR km$^{-1}$ replaced line [121].

**Combined Solution**

Figure B.8 shows the results of a combined optimization of grid reinforcement measures and curtailment of RES with the time-series-based method developed in this thesis. The interest rate for the line replacement measures is 4% and a price of 33 EUR MWh$^{-1}$ for the curtailment of energy is assumed. Up to year 4, no reinforcement measures are reasonable from an economic point of view. Line overloading is mitigated by curtailing a total of 2.1 GWh of energy resulting in a NPV of €0.06 million of OPEX for the curtailment. In year 4, 13.8 km of lines are replaced resulting in an annuity of €0.96 million per year and a NPV of CAPEX of €0.43 million. The NPV of TOTEX of the 10 year horizon is €0.49 million.

**Comparison**

Figure B.9 compares the NPVs of cash flows of the regarded investment period (left) and the DCFs of the final year (right). Results are shown for the worst case,
Figure B.7: SimBench Case Study - curtailment only solution assuming an interest rate of 4% and 33 EUR MWh\(^{-1}\) curtailment expenditures [121].

The reinforcement only, the curtailment only, and the combined optimization solutions. The highest total NPV of €3.69 million is expected when applying only curtailment measures. A reduction of 25% in costs with a NPV of €2.77 million is obtained by applying the worst case method. A NPV of CAPEX of €0.6 million is expected when considering only power line replacement measures in a time series simulation. The combined optimization of reinforcement and curtailment measures yields the lowest overall expenditures with a NPV of €0.49 million. The NPV of the total cash flows is 87% less compared to the curtailment only solution. The DCFs of the final year show that all solutions, except the curtailment only solution, yield the same expenditures in the final year. This indicates that the expenditures in this year result entirely from the CAPEX and a long-term curtailment strategy is no economic solution.

Sensitivity Analysis

The NPVs of the shown results are obtained based on fixed assumptions for the different parameters. To obtain a sensitivity on the TOTEX of one parameter, each parameter is varied while keeping the remaining ones constant. Figure B.10 shows a detailed sensitivity analysis on the NPV of TOTEX for the parameters: curtailment cost, depreciation, interest rate, and line cost per kilometer. Each parameter
Figure B.8: SimBench Case Study - combined solution of reinforcement and curtailment measures assuming an interest rate of 4%, depreciation of 50 years, 150 kEUR km\(^{-1}\) replaced line, and 33 EUR MWh\(^{-1}\) curtailment expenditures [121].

is varied between −90\% and 100\% of its initial value while fixing the remaining parameters to their original value. A steeper gradient of the resulting curve equals a high sensitivity to the parameter. Increasing the depreciation further from 50 years has the lowest effect on the NPV of the TOTEX. A decreasing depreciation, however, increases the TOTEX significantly. Varying the interest rate and the costs for curtailment has a similar effect on the NPV of TOTEX. Decreasing the costs per kilometer leads to a sharper reduction in the expenditures.
Figure B.9: SimBench Case Study - comparison of *curtailment only*, *worst case*, *replacement only*, and the *combined* method based on time series. The NPVs of the 10-year horizon (left) and DCFs of year 10 are shown (right) [121].

Figure B.10: Sensitivity analysis: Each parameter is varied between −90% to 200% of the initial values at 0% variation [121].
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The increasing share of renewable energy sources in the power system necessitates new planning methods for power systems. On the one hand, flexible operational measures must be included in planning. On the other hand, conventional planning measures have to be considered. In this thesis, a multi-year planning strategy for meshed high voltage (HV) systems is proposed considering operational flexibility as well as conventional planning measures. The defined optimization problem is solved by a hybrid optimization algorithm combining the advantages of heuristic and mathematical programming approaches. A reduction of the high computational effort of time series simulations is achieved by several strategies, which are integrated in the open-source tool panda-power. Furthermore, several machine learning algorithms are combined with the optimization of the established local search metaheuristic and a hybrid optimization model. The combination increases the applicability of the developed planning framework for a real HV power system model. Finally, two case studies show the applicability of the developed planning framework for a real HV power system model.