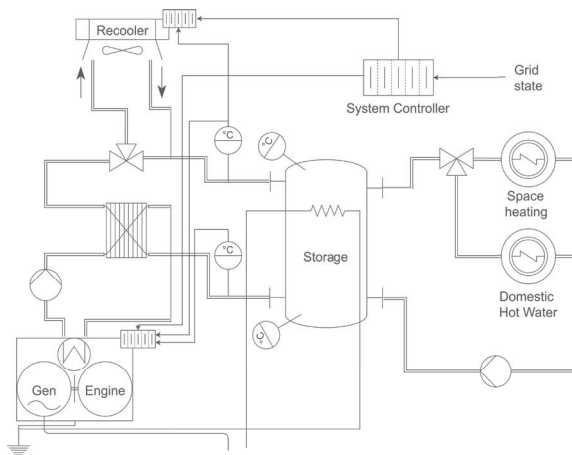


Design and Assessment of Grid-driven Distributed Cogeneration

Markus Schumacher
Institute for Energy Efficient Buildings and Indoor Climate



Design and Assessment of Grid-driven Distributed Cogeneration

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Abstract

The increasing deployment of renewable energy sources into the power system will lead to larger fluctuations in electricity supply. Currently, these are balanced by pumped hydro and conventional fossil power plants. The electrification of transport and thermal energy supply of buildings will impose new loads to the electric distribution grids. These developments will occasionally lead to overproduction of power and grid overload caused by heat pumps and electric vehicles, e.g. in cold winter nights. Besides such electrical demand a significant heat demand caused by buildings needs to be efficiently supplied. A contribution to an efficient heat provision could come from cogeneration systems. Additionally, cogeneration units could be utilized as flexible, distributed power plants that offer reliable and fully controllable supply while mitigating load induced grid congestions in the electric distribution system. To serve the aforementioned purpose, time resolved states of the electric energy system need to be determined and transmitted to the cogenerators. Hence, a dynamic CO₂ factor of the national power plant portfolio and the demand for congestion power in a corresponding local distribution grid need to be considered. Based on these status signals dynamic operation and control strategies are implemented.

In addition to the operation, the performance of a grid-driven cogeneration system depends on its output capacity and the size of the thermal energy storage. However, sizing and control strategies are mutually dependent. Thus, both aspects are simultaneously considered with respect to an optimal design method. The performance assessment of cogeneration is conducted based on CO₂ abatement cost and the potential for congestion management on distribution system level. The evaluation and optimization relies on dynamic simulation models coupled with a genetic optimization algorithm and is conducted for multiple building energy systems and boundary conditions. The systems' boundary conditions are determined by renewable energy sources penetration scenarios, distribution grid topology and different technology shares (e.g. electric vehicle and heat pump).

As a result, the optimal design under given boundary conditions is found and the influence of different factors like building application, power system context and control approach on the design and performance of the cogeneration system is analyzed. In this regard, general design implications are identified. To conclude the analysis an economic evaluation of cogeneration is conducted. An important measure in this context is the levelized cost of electricity for flexible power generation in comparison to conventional power plants. These serve as an indication for the marketing potential of grid-driven cogeneration in a given system context and signify the role of cogeneration in a future power system.

Kurzfassung

Der Ausbau der Erneuerbaren Energien führt zukünftig zu vermehrten Fluktuationen in der Stromerzeugung. Diese Fluktuationen werden bisher durch Pumpspeicher und konventionelle fossile Großkraftwerke ausgeglichen. Zusätzlich müssen mit der Elektrifizierung von Mobilität und Gebäudebeheizung neue elektrische Lasten in Verteilnetzen integriert werden. Dadurch drohen, neben einer zeitweisen Überproduktion von Strom, auch Überlastungen durch elektrische Lasten, z.B. in kalten Winternächten. Neben den genannten elektrischen Bedarfen besteht auf Verteilnetzebene gleichzeitig ein signifikanter Wärmebedarf, der möglichst effizient gedeckt werden muss. Eine Lösung zur effizienten Bereitstellung könnte die Anwendung der Kraftwärmekopplung (KWK) darstellen. Darüber hinaus könnte die KWK die Rolle von flexibel einsetzbaren, verteilten Kraftwerken übernehmen und auf lokaler Ebene lastinduzierte Netzengpässe vermindern. Um diese Funktion zu ermöglichen, müssen zeitaufgelöste Zustände des elektrischen Energiesystems bestimmt und an netzgeführte KWK-Systeme übermittelt werden. Hierzu werden ein dynamischer CO₂-Faktor des nationalen Stromerzeugungsparks und die Engpassleistung des lokalen Verteilnetzes, in dem das KWK-System installiert ist, betrachtet. Auf Grundlage dieser Zustandssignale können dynamische Betriebs- und Regelstrategien im KWK-System umgesetzt werden.

Regelungsstrategie und Dimensionierung bestimmen die KWK-Performance und sind voneinander abhängig. Beide Aspekte werden kombiniert betrachtet und die Bewertung der Performance geschieht anhand von CO₂-Vermeidungskosten und Engpassvermeidungspotenzial im lokalen elektrischen Verteilnetz. Zur Bewertung und Optimierung der Auslegung von KWK-Systemen werden dynamische Simulationsmodelle in Verbindung mit einem genetischen Algorithmus eingesetzt. Die Optimierung wird für diverse Gebäudeenergiesysteme und Randbedingungen durchgeführt. Die Randbedingungen sind durch Ausbauszenarien von Erneuerbaren Energien, die Netztopologie im elektrischen Verteilsystem und die Anteile unterschiedlicher Heizungstechnologien sowie Elektroautos gekennzeichnet.

Als Ergebnis erhält man eine optimale Dimensionierung für ausgewählte Randbedingungen. Der Einfluss verschiedener Faktoren wie Gebäudeanwendung, Struktur des Elektrizitätsnetzes und Regelungsstrategie auf Auslegung und Performance eines KWK-Systems wird untersucht. Grundsätzliche Auslegungsempfehlungen werden identifiziert. Abschließend erfolgt eine Wirtschaftlichkeitsbetrachtung der KWK-Systeme, in der die Stromgestehungskosten im flexiblen Einsatz mit denen von konventionellen Kraftwerken verglichen werden. Hieraus ergeben sich Rückschlüsse über die Vermarktungsmöglichkeiten und die zukünftige Rolle der dezentralen KWK-Technologie.

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Nomenclature

Abbreviations

ADR	active demand response
BES	building energy system
BPS	building performance simulation
CAPEX	capital expenses
CG	cogeneration
CHP	combined heat and power
CIGRE	international council for large electric networks
DG	distributed generation
DHW	domestic hot water
DLC	direct load control
DR	demand response
DS	distribution system
DSM	demand side management
EA	evolutionary algorithm
EEX	european energy exchange
ENTSO-E	european network of transmission system operators
ETS	emission trading system within the European Union
EV	electric vehicle
FLH	full load hours of operation or demand
GA	genetic algorithm

GB	condensing gas boiler
GCC	gas combined cycle
GOC	gas open cycle
HDC	heat duration curve
HEX	heat exchanger
HP	heat pump
HR	heating rod
HVAC	heating ventilation and air-conditioning
IQR	interquartile range
LCOE	levelized cost of electricity
LV	low voltage
MCP	market clearing price
MFH	multi family home
MILP	Mixed-Integer-Linear-Problem
MPC	model predictive control
MV	medium voltage
NES	national energy system
NPV	net present value
NSGA	non-dominated sorting genetic algorithm
OPEX	operational expenses
PFC	power flow calculation
PV	photovoltaic
RC	re-cooling
RES	renewable energy sources

SFH	single family home
SH	space heating
SPEA	strength pareto evolutionary algorithm
SPF	season performance factor of a heat pump
TES	thermal energy storage
VPP	virtual power plant
WEC	wind energy converters

Greek symbols

ϵ	evaluation function of genetic algorithm	
η	efficiency according to index	
γ	ratio of space heating demand to DHW demand	
λ	relative controller threshold level	
ω	overall fuel efficiency	
ϕ	probability	
π	enviroeconomic value of power	
ρ	density of water	$\frac{\text{kg}}{\text{m}^3}$
σ	power to heat ratio of cogeneration unit	
τ	period under observation	
ξ	electrification level in distribution system	%
κ	Capacity correction factor	
ν	Relative power generation	

Symbols

$\bar{w}$	relative work	
$\hat{P}$	installed capacity	W

Contents	Contents
A area	m^2
AC abatement cost	$\text{€}/\text{tCO}_2$
AF annuity factor	
C cost	€
c thermal heat capacity	$\frac{\text{kJ}}{\text{kg} \cdot \text{K}}$
D electricity demand	
E exergy provided by fuel	MWh
EX expenses	€
F Pareto front	
f factor for multiplication according index	
G grade of a Pareto front	
H hypervolume	
h height	m
I investment	€
i adequate target rate	$\%$ per annum
m mass	t
n number of	
$OPEX$ operational expenses	€
P power	W
p price	€ per unit
Q heat	MWh
r reference vector of Pareto front	
T temperature	$^{\circ}\text{C}$
t time	

V	volume	
v	velocity	$\frac{\text{m}}{\text{s}}$
W	work	MWh
x	genome vector of an individual	
z	Roughness exponent	

Subscripts

10	Measured at 10 m height
CO ₂	CO ₂ emission
a	air
abs	absolute
b	building
bot	bottom of a thermal energy storage
c	congestion
CG	cogeneration
cut	cut in
CX	cross
cyc	cycles
d	day
dem	demand
down	decrease of output
ECS	energy conversion system
el	electrical
eval	evaluation
force	forced operation

fuel	of fuel
g	gas
GB	condensing gas boiler
gen	generation
h	variable for heating technology
HC	hosting capacity
hor	horizon
l	national load
loss	grid loss
m	maintenance
max	maximum
min	minimum
MT	mutation
MX	multiplication
nom	nominal design working point
o	operation
occ	occupant
par	parameters
pop	population
r	residual
rat	rated conditions
ref	reference
rel	relative
RES	renewable energy sources

res	residual
rev	revision
room	room
set	set value
start	start up
stop	stopping
sup	supply
TES	thermal energy storage
th	thermal
top	top of a thermal energy storage
TRY	test reference year
up	increase of output
w	water
WEC	wind energy converter
x	genome vector of an individual
year	for an entire year

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1 Introduction

1.1 Motivation

The German energy system is undergoing significant changes in recent years, where the predominant aim is to reduce emissions within all fields of the economy. Besides the energy sector, which accounts for 36 % of the CO₂ emissions in 2018, the building and transport sector are very important in this respect. The transport sector has share of 19 % of the CO₂ emissions, whereas the building domain is responsible for 14 % (Umweltbundesamt, 2020). One dominant technological trend is the increasing share of renewable energy sources (RES) in the electricity production from both wind and solar power. In order to utilize the electricity generated by RES the energy demand needs to rely on electricity to a greater extent. Hence, the electrification of transport and building energy supply is a second important pillar in the implementation of the energy transition towards lower CO₂ emissions. In the power system domain the fluctuating nature of RES is of great importance, since the balance of generation and load needs to be ensured at all times. In this respect, building energy systems (BES) that are coupled to the electricity system, e.g. heat pumps (HP) and distributed cogeneration systems (CG), have the potential to support the balancing of generation from RES and the demand. For instance, HP systems could be used in demand side management (DSM) schemes to consume electricity when there is an excess.

However, an important issue is the time resolved consideration of the RES potential. Especially in low voltage (LV) distribution systems (DS) the major part of the RES power production will be covered by photovoltaic (PV) power, which is naturally unavailable at night. Furthermore, economic aspects of power generation in large centralized power plants need to be considered. These will face significant reductions in utilization, which make the operation of existing and the investment into new conventional power plants less attractive. In combination, lower backup capacities and an increasing electrification of the energy demand from transport and the building domain could lead to a lack in power production that would need to be covered by electricity imports. Further, the introduction of new electric loads, such as HP and electric vehicles (EV), are very likely to happen on the DS level. This has the potential to put high stress on the electric DS and endanger the reliability of supply.

In this context, distributed CG systems could play an important role. They have a beneficial CO₂ balance since they use the supplied fuel to produce both heat and power. In addition to that, CG systems equipped with a thermal energy storage (TES) can shift their operation to favorable times, where power has a relatively high value. The question that arises with this

concept is how an actual CG system shall be designed and operated to suit the requirements that are imposed by the surrounding energy system. To deal with that question this thesis will analyze the design and operation of CG systems in different setups and under diverse boundary conditions. The thesis will present an approach on how to couple the time-variant state of the national energy system (NES) and the local DS with the operation of distributed CG devices to reduce CO₂ emissions and to mitigate grid congestion, that are likely to occur in future LV networks. Considering a coupled operation, an approach for the optimal design of distributed CG in residential applications is presented. The predominant, and yet conflicting, aims of the optimization are low CO₂ abatement cost and a high balancing potential for the local DS.

1.2 Literature review

The following sections provide an overview of the literature that is considered in this thesis. In a first part the focus is on distributed generation in general. Definitions and the common terminology are presented and examples of practical applications are given. Afterwards, the transition of the energy system is considered. Recent trends in the energy supply and demand are investigated. Depending on the actual application CG serves different purposes. Hence, the performance assessment of the technology differs as well. Common methodologies on that matter are presented. A core aspect of this thesis is an analysis of the design of grid-driven CG. Therefore, existing design approaches for HVAC technologies are presented, followed by a review on the integration of BES and the electricity system.

1.2.1 Distributed Cogeneration: Definition, technology and application

Distributed CG combines the concepts of distributed generation (DG) and CG. However, the distinction of these concepts is not always used consistently. Further, different applications and scales of CG are observed in practical implementations.

The concept of DG is presented in Ackermann et al. (2001). Just like the definition of CG, diverse interpretations of the term DG are found. These definitions differ with respect to location, applied generation technology and rated power. Their work finds that many of the characteristics that are currently used cannot precisely define DG or even exclude each other. However, some aspects are widely accepted and can be used to form a consistent definition. They conclude that DG can be defined as electric power generation within distribution networks or on the customer side the network. Based on a survey Pepermans et al. (2005) describe existing small scale generation technologies and corresponding issues and benefits. According to them, DG has the potential to reduce the environmental impact of electricity generation. It will not be able to avoid or even postpone the need for new transmission lines,

as the grid has to be an available backup supply. They derive a general definition of DG as an electric power generation source that is connected directly to the distribution network on the customer side of the meter. This definition includes small CG, but PV or small scale wind power as well.

According to Onovwiona and Ugursal (2006) CG which is also known as combined heat and power (CHP) is defined as "[...] the simultaneous production of electrical or mechanical energy (power) and useful thermal energy from a single energy stream such as oil, coal, natural or liquefied gas, biomass or solar". They categorize residential CG applications into single family home (SFH) ($< 10 \text{ kW}_{el}$) and multi family home (MFH) ($10\text{-}30 \text{ kW}_{el}$). In their review they found reciprocating engine and fuel cell based CG to be most likely successful. Further they identified the most important performance factors of CG, i.e. efficiency, reliability, availability, maintenance requirements and emissions.

Schaumann and Schmitz (2010) give a broad overview on CG technologies and suitable applications and elaborate on the environmental and economic performance. With respect to the unit size they do not emphasize on small to medium scale CG, but rather address the entire capacity spectrum which ranges from 1 kW_{el} to over 500 MW_{el} . These large scale technologies, however, do not suit the purpose of this thesis. Isa et al. (2018) consider different scale CG in the context of microgrids. According to them, reciprocating internal combustion engines are a suitable choice as a prime mover technology, for small scale applications such as residential building. A major advantage of this technology is the proven and robust technology. Further they realize quick startups, show good load following and part load abilities. In addition, CG based on internal combustion engines are available in a wide capacity range.

As already shown in Pepermans et al. (2005), Driesen et al. (2006) discuss main benefits and issues of DG. Based on this discussion the possible impact that DG has on the distribution grid is evaluated by performing a small case study on an existing network. They show that besides the electrical power also the point of connection and the type of DG (inductive or synchronous) has a significant effect on the grid (especially voltage) stability. Further they mention that some issues of DG that are stated in literature originate from the fact that DG is assumed to be non-dispatchable, which is not necessarily the case nowadays.

1.2.2 Transition of energy systems

Currently, the entire energy system in Europe is in a transition phase from a fossil fuel-based towards a renewable supply. Especially the power systems face challenges due to this process and will significantly change within the next decades. In addition, the energy demand of heating and transport will be supplied by electricity to an increasing extent. Bossmann and Staffell (2015) show how future countrywide electrical loads can be modeled and predicted. They analyze influencing factors on the overall demand such as the predominant heating tech-

nology or transport technologies. Further they analyze load dynamics of the aforementioned technologies. To emphasize the importance of these dynamics, they study two different countries which show a very different ongoing energy transition (i.e. Germany and Great Britain). They expect a decarbonization induced by a shift towards electric heating and transport technologies. Further they conclude, that this shift will lead to much higher electricity demand peaks and an increasing demand for flexible generation capacities.

An analysis by Hedegaard et al. (2012) investigates the effects that a substantial integration of EV will have on the electricity systems. Several Northern European countries including Germany are considered. The results show that for countries with a high energy density, such as Germany, the renewable generation from wind power will not be able to supply major shares of the additional electricity demand of EV. In fact, only after 2025 this situation might change. Before, however, additional fossil-fueled capacity from hard coal and gas will be necessary.

According to Isa et al. (2018) the transition of the electricity system towards smart grids is promising. They expect microgrids to reduce both carbon emissions and utility bills. In that sense, smart grids can be an enabler for the development of grid-oriented CG.

1.2.3 Performance assessment

With a transition of the energy system new challenges arise. These challenges will be encountered using new approaches and technologies. To be able to evaluate the potential of such novelties, appropriate assessment methods need to be applied. CG is considered as a candidate technology. A review on possible performance assessment methods is presented in this section.

Usually, HVAC technologies such as CG and HP are evaluated from a cost, primary energy or emission perspective. In that sense de Paepe et al. (2006) analyze different CG technologies, e.g. reciprocating engine, for their potential to reduce the primary energy consumption, CO₂ emissions and cost. Regarding the emission assessment they compare CG with the separate production of heat and electricity by GB and central power plants. They find that the potential emission savings are clearly determined by the power generation structure of the NES and the corresponding emission intensity. Further, CG technologies differ widely both in economic and environmental performance. Although the work addressed the importance of the NES structure no appropriate dynamic signals for the emission intensity or the primary energy factor are considered.

The need for dynamic CO₂ factors is addressed in the work of Patteeuw et al. (2015). They analyze the CO₂ abatement of electric HP in different building setups. For that purpose, an integrated modeling approach that considers the BES and the NES of Belgium is developed. The model is implemented as a mixed integer linear problem (MILP) and considers the effect

that a large deployment of HP has on the electricity system. The results show CO₂ abatement cost in the range of 100 to 1500 €/t which largely depend on the considered seasonal performance factor (SPF). A method to determine a time variant primary energy factor for power is presented in Panitz et al. (2015a) and Panitz et al. (2015b). Commonly used assessment methods for grid-coupled HVAC technologies like HP usually rely on constant primary energy factors. According to the presented work this practice does not correctly consider the actual mechanisms of the electric energy system. Instead, the proposed dynamic primary energy factor that explicitly considers the current power generation mix should be applied to assess grid-coupled supply concepts.

In that sense, Stinner et al. (2017) present a new primary energetic evaluation method that accounts for the time-dependent availability of renewable power production. Additionally, restrictions in the electric DS are explicitly considered. The effects that different technology shares have on the average primary energy factor are presented in detail. With respect to the environmental performance of BES they demonstrate the positive effect that TES have. They increase the operational flexibility of the BES and thus enable the exploitation of phases that show a low primary energy factor.

In Morales-Durán et al. (2017) an optimization approach for district CG systems is presented that considers the assessment of both financial and environmental aspects. To this end, they investigate pollutants, like green house gas emissions and the CG system's environmental impact. For that purpose they apply a life cycle assessment method. However, the interaction with the electric DS and NES are only weakly addressed using static characteristics. Time-resolved emission factors or prices are not considered.

1.2.4 Design of cogeneration systems

This section addresses the design methods for CG systems. Significant differences in the methodologies are observed. Traditional approaches mainly consider economic and environmental aspects using heuristic methods. Haeseldonckx et al. (2007) show the positive effect that the application of TES have on the environmental performance of a heat-driven residential CG system. In addition, TES positively affect the cycling behavior and expected service life of a CG unit which is an important aspect in relation to grid-driven CG systems. Further they propose a maximum rectangle sizing method that maximizes the heat supplied by the CG system in relation to the sorted heat duration curve of the demand.

Guidelines on the design of micro-CHP are found in Bianchi et al. (2012). They consider different prime mover technologies according to their power-to-heat ratio. The variable design parameters within the analysis are the thermal output of the CHP unit as well as the TES volume. Thermal demand curves of different peak loads and annual energy demands are considered. A simulative analysis is conducted to assess the CHP setups with respect to their

primary energy demand and cost. The results show that economically feasible CHP systems are more likely to be obtained in large residential building applications such as MFH. These enable larger unit sizes and thereby lower marginal investments. Further they show, that monovalent CHP systems without auxiliary peak load boilers are achievable.

In contrast to these general guideline, Gelezenis and Mavrotas (2017) present an approach for the analytical determination of an optimal dimensioning of residential CG systems. They state that the limited market penetration of CG in residential buildings is mainly due to improper dimensioning, but also due to high equipment cost. In their study they investigate a heat-driven CG system that sells excess electricity to the grid. They find the CG unit's optimal capacity to be in the range of 30 to 50 % of the building's maximum heat load. Generally, the shape of the sorted heat duration curve and the part load efficiencies of the CG systems have the largest effect on the optimal sizing. According to them, energy prices only have a minor influence on the economic performance. However, no dynamic factors, like power prices or LV network limitations are considered in their work. The assessment was conducted with a focus on economic aspects. Therefore, the general findings with respect to the optimal dimensioning are not necessarily valid in a dynamic evaluation context.

Cho and Lee (2014) introduce a simple sizing method that is only applicable for heat-driven CHP systems in a static system context. External conditions, e.g. energy prices and thereby the current value of power are constant over time. Nevertheless, the results of this analytical approach show a good performance in comparison to numerically optimized methods. The approach is compared to the maximum rectangle approach by Haeseldonckx et al. (2007) claiming it to be oversimplified in terms of economic considerations.

Urbanucci and Testi (2018) analyze the effect of stochastic input parameters on the robustness of design optimization results and compare it to a deterministic approach. Their design approach consists of two separate steps. First a size selection which is followed by a control optimization that aims at the expected and the worst case cost saving. They show the need for probabilistic approaches since the results vary significantly and lead to an oversizing of CHP units. Aspects like part load efficiencies were considered, however detailed controls and dynamic physical effects, e.g. TES stratification were not addressed. Neither the actual connection to an electricity network nor the environmental performance are considered.

According to Voorspools and D'haeseleer (2006) traditional CG sizing methods, like the maximum rectangle, do not correctly reflect the energy and emission savings potential since they leave out the interaction with the NES. They conclude that prolonging the annual operation, by either reducing the CG unit size or by dumping excess heat, is a promising measure to improve the interaction with the NES. Thus, a reduction of the primary energy demand and CO₂ emissions might be obtained at the same time. However, they do not consider the concept of grid-driven or dispatchable CG to improve the NES interaction. Further, they use a simple CG model, in which all CG devices in the system are represented by only one virtual

CG unit. With respect to the complexity of the power system and its actors this approach seems questionable.

In contrast to the aforementioned heuristic or analytical design approaches, optimization methods are increasingly applied to the design of BES. Caldas and Norford (2003) give an overview of different applications of genetic algorithms (GA). These range from design of building and HVAC systems to the operation optimization for a short time horizon. However, for scheduling problems longer than some hours the applicability seems to be limited. This issue is partially addressed by Evins (2015), who present an iterative combined building design, energy system sizing and operation approach. On an upper level, first a GA is used to optimize the building and plant design with a given operation schedule. On a lower level, a dispatching problem, formulated as a MILP, is solved. This results in the aforementioned operation schedule. The solutions of the MILP are processed to the GA again and a new population is formed. Although this approach enables the optimal control of a BES, it is not able to consider non-linear effects.

Another MILP-based study is conducted by Patteeuw and Helsens (2016). They investigate a combined sizing approach, in which both the design and operation of residential heating systems is optimized. They use a MILP which also considers external electricity generation with a variable electricity mix. Furthermore, different temperature levels of the heating systems are considered, which did not prove to have substantial added value. The approach looks at a NES and does not consider any electrical grid limitations in detail. However, RES-induced grid congestion is taken into account in a very simplified way based on must-run power plants, the RES production and the aggregated demand. The authors conclude, that TES for space heating have a negative effect on the emissions rating and the annuity of supply as well.

Pruitt et al. (2013) explain how CG technologies face the challenge of appropriate sizing and control in a dynamic energy system context. According to them, important dynamic performance characteristics of CG systems are often disregarded. Therefore, in design analyses suitable approaches, e.g. MINLP, need to be utilized. Especially characteristics that describe the time-variant behavior, such as startup and shutdown times, ramping and part-load efficiencies, are of major importance in such a dynamic system context. A result of disregarding these effects can be a significant under- or overestimation of the optimal device sizing or even infeasible design parameters. However, when considered, the model complexity especially of MINLP grows and makes them difficult to solve.

Gimelli et al. (2017) analyze the optimal design of CHP systems at the example of hospital facilities in Italy. They use a GA in combination with a CG calculation algorithm towards the optimization of primary energy savings and simple payback time of the investment. The robustness of the obtained optimal solutions is investigated by introducing stochastic environmental parameters using probability functions. The results show that the sensitivity of the optimal solution towards the input parameters is not negligible.

In Ooka and Komamura (2009) an optimal design method for energy systems is presented that covers both sizing and operation. The objectives of the optimization can be manifold, e.g. energy consumption or CO₂ emission. Non-linear models are used to represent the energy systems which leads to the utilization of a GA. Since GA are dependent on the combinatorics of a given problem, the operation optimization was only feasible for a single day in a one-hour resolution, leading already to 24 decision variables. However, the comparison of the optimization results with the global optimum found through a "comprehensive inquiry method" revealed a good agreement. Very complex energy systems can be optimized using the presented approach. However, the low time span drastically limits the applicability.

A study by Lund and Andersen (2005) on the design of CHP systems shows that larger units are better able to cope with dynamic power tariffs. In addition, they find that an increasing uncertainty in the power prices leads to larger optimal storage sizes. Hence, they propose to invest in larger TES volumes to meet future requirements. However, the results are not obtained using sophisticated optimization methods. Further, they do not consider the importance of CG operation.

In the sense of an improved interaction with the NES, Schüwer et al. (2016) analyze the ability of distributed CG systems to participate in the German minute reserve market. Residential and non-residential buildings are considered. A heat-driven standard sized system is compared to three different flexible systems, one among them with re-cooling. Results show, that a significant technical potential could be achieved at the sacrifice of emission performance. Further the economical perspective on this was not considered in detail.

1.2.5 Integrated operation of buildings and power systems

The literature review of the previous section reveals that the integration of building and grid operation gained importance in recent years. However, different concepts exist to trigger the inherent operational flexibility of BES to serve a specific purpose of the power system.

From a theoretical perspective Makarov et al. (2012) provide an overview of the flexibility demand. They demonstrate that flexibility demand signals that originate from high shares of RES can be decomposed into various frequencies using Discrete Fourier Transformation. Thereby, flexibility demand for short-term, intraday and long-term balancing are identified. This approach is applied to a power flexibility demand but might also be used to harness dynamic CO₂ factors. Further, this approach might be used to categorize different congestion power demands in a local LV grid.

Regarding the triggering of flexibility provision Patteeuw et al. (2016) assess different methods for load shifting to enhance the electrical grid operation. An integrated optimization algorithm is used to obtain a best-case scenario by means of operation cost savings. This best-case scenario serves as baseline for the assessment. Based on this, a direct load control (DLC)

approach and several price-based building control approaches were compared to the base line. Results show that DLC performs best and might be combined with price-based methods. Houwing et al. (2011) compare a demand response (DR) control approach in conjunction with dynamic electricity prices with a standard heat-driven CG system. The DR control approach is realized by a model predictive controller (MPC) that comprises a MILP. Results show that dynamic tariffs can be exploited using DR. Further, they conclude that the fluctuation of the considered price signal is of major importance for the DR's performance.

In Cooper et al. (2014) different indirect DSM methods are applied in a district energy systems comprising 128 homes. The DSM approaches are combined with both HP and CG systems. Results show that only a minor impact on the emissions can be expected from DSM. Nevertheless, a reduction of the peak electrical demand within the DS is found. In a HP dominated district DSM alone is not able to mitigate congestion. However, the combination of HP and CG systems is able to supply the heat demand of the district without exceeding the grid capacity limits.

Widmann et al. (2017) propose a new approach for the operation of CG systems which is led by electricity demand instead of heat. Using a simplified forecasting algorithm for thermal and electrical demand, they calculate a set of possible operation schedules. The time variant TES capacity is considered in this approach. The most suitable schedule to maximize on-site power consumption is chosen. To cope with the forecast error and a consequently weak scheduling, ad hoc events are introduced, at which the CG device can be forced into or be prevented from operation. In their work the full usage of the produced thermal energy is seen as a strict limitation in order to achieve energy efficient operation. However, considering a dynamic CO₂ scheme for evaluation instead, could make this limitation obsolete in future applications.

Ruiz et al. (2009) propose an optimization algorithm based on a linear problem for the DSM of thermostatically controlled devices. They show that changing the set temperatures within a building is exploitable for DSM purposes. Based on this DLC approach a virtual power plant is implemented using thermostatically controlled devices. The most common methods for congestion management that are currently applied in distribution grids are presented by Huang et al. (2014). The obtained results identify voltage deviations and asset overload to be the most relevant congestions. These are either induced by concurrent power injection of RES or by the increasing electric load of HP and EV. With respect to DSM measures they distinguish indirect and direct methods that are both in responsibility of the distribution system operator. They conclude that first grid reconfiguration and reactive power control should be applied. Only if those still leave the grid in a congested state, market-based and active power control should be used.

As already mentioned in Cooper et al. (2014) CG and HP systems might be a promising combination. Beyond this, Ribberink and Entchev (2014) analyze in what extend the up-

coming trend towards electrification of private transport and CG in residential applications could benefit from each other. They identify a general synergy, which strongly depends on the considered charging scenarios though. A sensitivity analysis was only performed for non-HVAC electricity demand, although thermal demands would have a major influence on the CG operation. However, the CG sizing was done with rule of thumb rather than an optimal approach. Further, they found that charging profiles with low power and longer duration suite the CG operation better. To some extent this is contradictory to recent trends in charging infrastructure.

The combination of EV and HP with CG is analyzed by Rosato et al. (2017). A rather holistic analysis on the grid interaction, global emissions and primary energy use as well as operating cost is conducted. The obtained results show that a mitigation of the negative grid impact of EV and electric HP can be achieved by CG systems. However, an exact quantification using a power flow calculation (PFC) is not considered. Besides, the economic performance analysis falls short of the necessary system investment. The CG design within this study is not optimized which leaves additional potential for improvement.

1.3 Objective and structure

One of the main objectives of the presented work is to analyze which potential grid-driven distributed CG can offer to accompany the increasing share of RES in power generation. Since the overall goal of the German energy transition process is the reduction of CO₂ emissions, the possible contribution of individual buildings in specific conditions will be analyzed. In this regard, economic aspects play an important role. When reducing emissions, technologies with low CO₂ abatement cost should be preferred to minimize social cost. In this work, the actual cost for CO₂ abatement that can be achieved by grid-driven CG systems are determined. Additionally, its potential to mitigate stress on the DS, induced by the electrification of transport and heating, is investigated. Furthermore, this work will address the question if CG devices can be seen as a fully controllable and reliable power supply to the surrounding energy system, while fulfilling the thermal needs of buildings.

To holistically cover aspects of the DS and NES level, this work presents a combined design optimization approach that incorporates the conflicting goals of low CO₂ abatement cost and high grid congestion mitigation potential. The parameters to be optimized cover the CG unit capacity and TES sizing. In addition to that, operation-related control parameters that effect the device's grid interaction will be included in the optimization as well.

Figure 1.1 shows the structure of this thesis. The first section provides an overview on the considered research topic. It emphasizes the motivation for this thesis explaining the challenges that exist concerning future energy systems. A literature review presents the

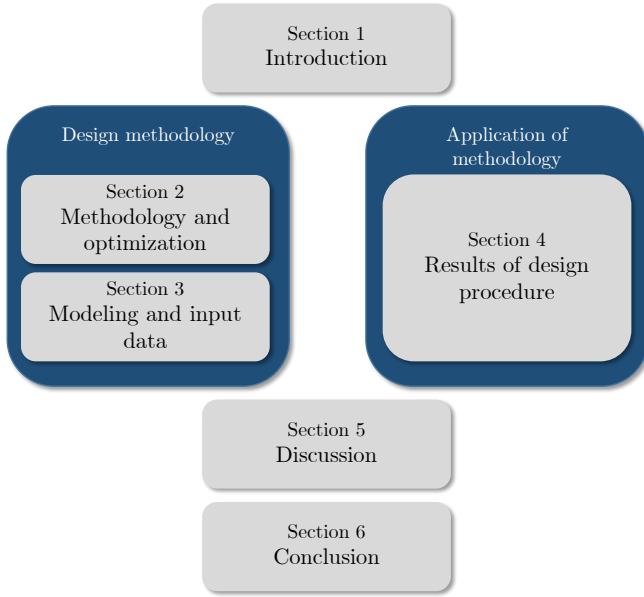


Figure 1.1: Structure of the thesis.

current state of research in various subdomains that are linked to the topics considered in this thesis.

Based on the introduction, the main part of the work comprises two parts in which the design methodology and its application is explained in depth. The design principles in section two deals with the methodology that was chosen for the integration of a time dependent energy system state and the design of distributed CG devices. Besides, the optimization approach for CO₂ abatement cost on the one hand and grid congestion mitigation on the other hand is presented. The considered energy system is subject to a high complexity, which is why the analysis within this work relies on models. In that sense, boundary constraints in which the design optimization is performed need to be simplified. This way, the complexity which is introduced by the mutual design dependencies of individual CG systems in a district can be dealt with. The application of a model-based approach allows first conclusions without the need for a costly real world implementation. Section three presents the BES, NES and the DS models that are used to implement and apply the methodology of this study. In addition to models, the utilized input data is presented.

Following the above design approach the optimization results for various scenarios are investigated in section four. They give a clear indication on the achievable CO₂ abatement cost and the grid congestion mitigation potential that a specific CG system can accomplish. Based on an analysis of the individual design variables common principles are formulated. Afterwards the results and the main findings of a grid-driven design approach are discussed in section five. The final section concludes this thesis and gives an outlook on future research questions that need to be tackled.

2 Methodology and optimization

In this chapter the methodology for the design of grid-driven residential CG systems is presented and the assumptions on the boundary conditions are described. The relations of the system in which CG is analyzed is depicted in figure 2.1. An important element is the power system and its current state which is presented in section 2.1. The NES and DS which form the power system in this thesis are explained in the subsections 2.1.1 and 2.1.2.

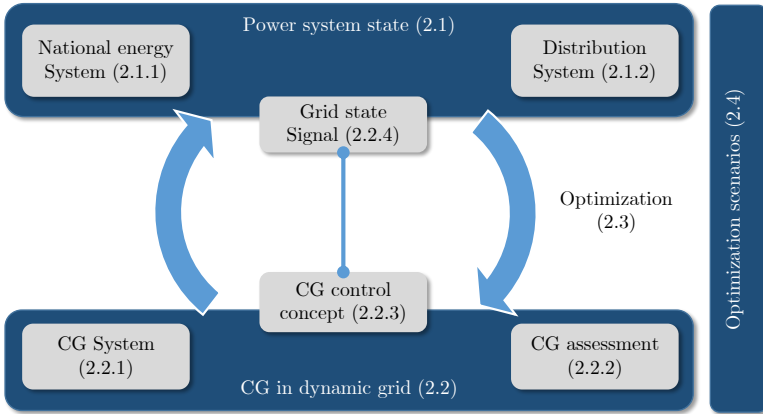


Figure 2.1: Key elements of the applied methodology.

Section 2.2 refers to CG that is operated in a dynamic grid context. First, the CG unit and additional components are addressed in section 2.2.1. Afterwards, the applicable assessment method is presented in section 2.2.2. Due to a dynamic energy system that surrounds a CG unit, the device itself needs to be able to dynamically react on changing conditions. To account for this aspect, the control concept of grid-driven distributed CG systems is presented in section 2.2.3. The counterpart of the CG control is the grid state signal. It is thoroughly elaborated in section 2.2.4. Based on the former two elements an informational link of the power and CG system is established which consequently enables a grid-driven control concept.

The CG design is optimized within this relational context. Therefore, section 2.3 describes the optimization approach that is considered in this work. An overview of the conducted optimization scenarios in section 2.4 concludes the methodology.

2.1 Determination of power system state

At first, a view on the NES emphasizes the mechanisms of a large scale power system and its market. The expected impact of the NES on the operation of CG devices is explained. Besides the economic view on the power markets, a new approach of deriving a dynamic ecological power system state based on the power plant dispatch will be presented. Together, these power system indicators form an enviroeconomic state that combines both environmental/emission and economic aspects. Second, technical aspects of the power DS will be emphasized and potential challenges occurring with an ongoing electrification of demand and a large deployment of RES in power generation will be introduced.

2.1.1 National Energy System

This section provides an overview of the NES and its mechanisms that determine the time variant value of electricity. From an economic perspective this value of power is defined at every point in time by the market equilibrium of supply and demand. In adoption of these financial mechanisms, a methodology that uses the same principles to define a time-variant emission value of power is presented on the basis of Panitz et al. (2015a) and Panitz et al. (2015b).

In the present NES a power demand is given and the necessary supply to cover this demand is considered accordingly. However, with a growing share of RES in power generation and its feed-in priority only a decreasing part of the electricity supply can be fully controlled. In fact, the major share of Germany's renewable power generation is based on variable wind power and PV. Hence, it is not able to increase its output on purpose. Systematic reductions, however, are possible and already applied today (Bundesministerium für Wirtschaft und Energie, 2019).

To clearly distinguish the load that needs to be covered by conventional, fully controllable generators and the overall load, the term residual load is defined as follows:

$$P_{\text{res}}(t) = P_1(t) - P_{\text{RES}}(t) \quad (2.1)$$

Based on this residual load the current supply structure within a NES can be found by applying the merit order, which is schematically depicted in figure 2.2

The demand curve D_1 represents the current load situation in the NES, whereas the supply curve is defined by the variable cost of power generation in increasing order. Looking at the gradient of curves it can be noticed that the supply curve is price-elastic. In contrast to that, the demand curve shows only very little price elasticity. For different generation technologies that are present in a market the variable costs differ and are dominated by the

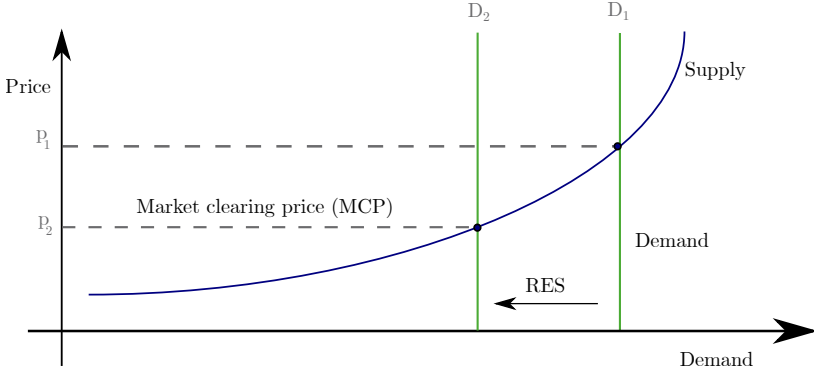


Figure 2.2: Power pricing in the NES following a merit order approach.

fuel costs of the considered plant. Furthermore, the obligation to purchase CO₂ allowances has an increasing effect on the variable cost. The current price of electricity p_1 according to the merit order can be found at the intersection of both curves which states the market clearing price (MCP). In contrast to a NES that is purely supplied by conventional power plants, the introduction of RES leads to a residual load shift and the demand curve is moved to the left (D_2). Consequently, the corresponding MCP is fixed at p_2 . This so called "merit order effect" occurs due to almost zero marginal production cost of RES and plays a dominant role in the power price settling for future scenarios. Therefore, the merit order effect needs to be incorporated into the methodology of this work.

Based on the aforementioned merit order the power plant dispatch for a certain prediction horizon is done by the operator of a partial transmission grid. Different restrictions on the assets' operation capabilities, such as startup times and power ramping, are considered in this approach. A detailed overview on the assumptions that are made is presented in chapter 3.

However, neither demand nor supply can be predicted perfectly, which requires further mechanisms to ensure the matching of power supply and demand. These mechanisms are implemented in the balancing market that can be subdivided into three different sub-markets, namely primary, secondary and tertiary balancing power. Each sub-market puts different requirements regarding operational characteristics on the participating assets. In the methodology of this thesis forecast errors on loads and RES production will not be included. The implementation of a power market model relies on the merit order concept accompanied by technical restrictions induced by different power plant technologies. As the NES model in section 3.2 shows, none of the three balancing market parts will be considered in this work.

With a full description of the power market's electric loads and power plant portfolio and the open source software "PyPSA: Python for Power System Analysis", a unit commitment and power plant dispatch problem can be formulated and solved (Brown et al., 2018). This optimization problem is implemented as a MILP. It can be solved using the commercial software Gurobi (Gurobi Optimization, 2020). Following the above approach, a cost-optimal power plant dispatch for a certain period of time can be calculated. It provides an exact overview of the current generation mix for the considered period (Cebulla and Fichter, 2017). Based on this power plant dispatch, different approaches can be used to define the current state of the NES and thereby the enviroeconomic value of power. In this work a marginal and a mixed approach are distinguished.

In the mixed approach, the calculation of time-variant power prices and CO₂ emission factors use the average of all power plants that are in operation at a certain point in time. In contrast to that, the marginal approach defines the current power system state solely on the properties of a so-called marginal power plant. This marginal power plant is accountable to cover any change in the NES's current load by either increasing or decreasing its current power output.

The presented methodology assumes that the marginal power plant can always be identified, enabling the calculation of the economic and ecologic state of the power system for an arbitrary supply situation. An example power plant dispatch and the resulting power system state is shown in figure 2.3 for four days in spring. The state is based on the supply and demand situation of the reference year 2017 and covers a period from Friday to Monday. In the upper part of the figure the residual load within the NES and its corresponding power plant operation is depicted. The power plant dispatch clearly shows the technologies' different purposes with nuclear and lignite as base load, hard coal and gas-combined-cycle (GCC) as medium load and gas-open-cycle as peak load power plants. The middle part shows the resulting generation prices of the generators involved to cover the residual load subjected to their operational restrictions. Here, the marginal curves correspond to the variable cost of the most expensive generator in charge, which is the marginal power plant. In the lower part the CO₂ factors that were derived based on the above dispatch are depicted. Similarly to the calculation of the power price, the calculation of the dynamic CO₂ factor accounts for a marginal and a mixed approach.

Following the marginal price curve from the beginning, first a low price phase of around 15 EUR/MWh is observed. After that a step can be identified which results from a technology switch of the marginal power plant. The aforementioned marginal energy unit is now being supplied by a GCC power plant instead of the base load lignite power plant. Consequently, this leads to a significantly higher price due to the comparably higher fuel cost of the GCC technology. Looking at the CO₂ emissions of that first day, an opposite trend can be seen. A phase of CO₂-intensive power supply determined by a lignite power plant is followed by a

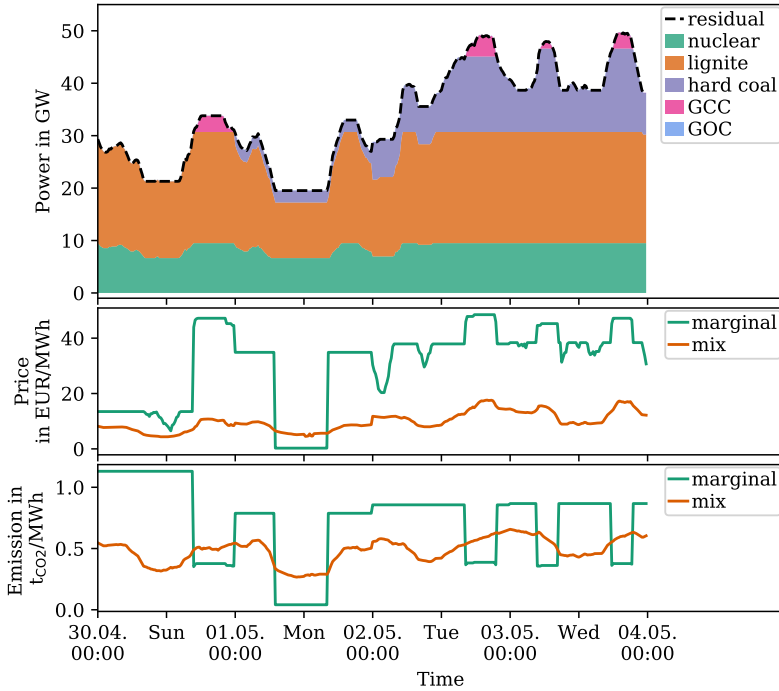


Figure 2.3: Conventional power plant dispatch resulting in power price and CO₂ intensity.

rather low emission phase of GCC operation. Here, the favorable carbon share of natural gas in comparison to lignite and the high electrical efficiencies of GCC power plants take effect.

In contrast, the aforementioned mixed approach reflects the average variable cost and CO₂ intensity of all generators involved to cover the residual load. This leads to smooth curves without significant steps. The trend of both curves is dominated by the technology that currently has the highest share in power generation. Since by definition, base load power plants contribute with a comparably large amount to the power supply in a NES, the power price and CO₂ intensity are dominated by these technologies. In comparison to the marginal curves, this leads to significantly lower average price and emission values. Looking further into the course of the marginal price and CO₂ intensity, a drop to values close to zero can be identified.

This effect, however, can not be explained using the traditional marginal power plant concept as above. Nevertheless, an explanation is found considering the dispatch of RES which is

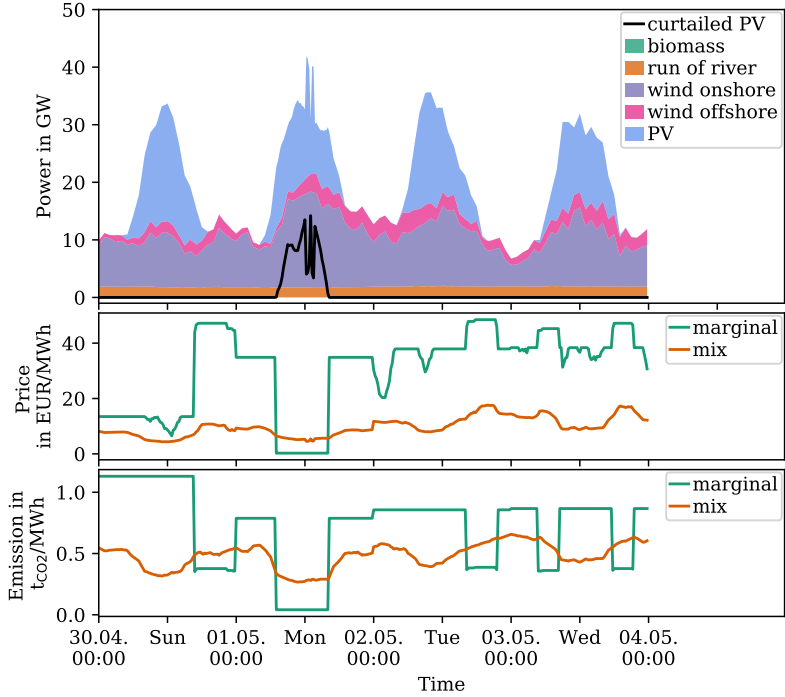


Figure 2.4: Influence of RES dispatch and curtailment on the power price and CO₂ intensity.

shown in figure 2.4. The upper part of the figure shows the RES dispatch. Besides the different RES technologies that are present in the German NES, the curtailment curve of RES is depicted. This curtailment is a controlled output reduction of RES due to grid overload in subsystems of the NES. Furthermore, curtailment is used in the presented methodology to deal with imbalances of power supply and demand. The imbalance, however, is not necessarily caused by a negative residual load, which the example period confirms. Instead, the cost-optimal power plant dispatch in the considered situation prevents a costly cycling of base load and medium load power plants. In this case, the integration of the full PV potential would lower the CO₂ emission but would in turn lead to higher overall generation cost due to power plant cycling. An additional marginal power demand would not be covered by increasing the electrical output of the marginal power plant as mentioned above. Instead, the curtailment of RES could be reduced, setting the price and emission intensity to values close to zero. As explained above, both these values are dominated by the CO₂ intensity of the utilized primary energy, which is solar radiation for the examined case.

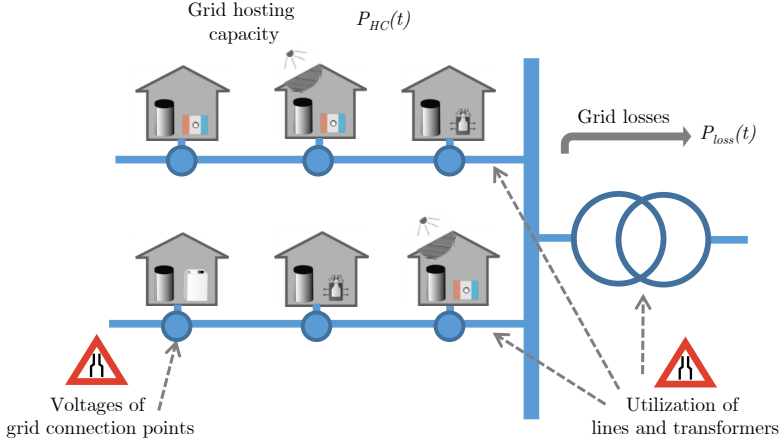


Figure 2.5: Typical congestion situations and their positions in a LV distribution grid.

To determine future power system states with different boundary conditions projections need to be enabled. For that purpose, however, an adaptable model is needed that incorporates all effects that were described above. Variations of electric load curves and the available generation portfolio needs to be changed to account for structural changes that will be introduced by the ongoing energy transition. Further, the consideration of consistent weather conditions for both the NES and CG systems are a prerequisite. This way distributed CG can be assessed and designed in dependence of the power system state. The aforementioned variability is a crucial element of the presented methodology. To represent the above effects in an efficient modeling approach is considered which is presented in the following chapter 3.2.

2.1.2 Distribution System

The transition of the electric energy system takes place on the MV and LV level for the most part. Especially the introduction of new electric loads, such as EV and electric HP, are expected to have major impact on the planning and operation of the electric DS (Schlösser, 2019). Beyond that, the power injection by PV systems into the DS is expected to bring new challenges (Widén et al., 2010). Further, the aforementioned technologies tend to have a high concurrency which is determined by environmental conditions (solar irradiation and ambient temperature) and/or user behavior (power usage for EV charging) (Wiest, 2018).

A schematic of a DS is shown in figure 2.5 emphasizing on common grid congestions that are likely to occur. For DS with significant shares of EV, HP and PV systems grid congestions

like capacity overloads of lines and assets, e.g. transformers, are expected. Further, voltage deviations can be an issue due to high PV power injection or high electric loads that originate from EV and HP (Brunner et al., 2013)(Schlösser et al., 2015). These grid congestions endanger the reliable operation of DS and need to be dealt with. Today the primary solution to ensure a reliable LV grid operation is reinforcement of network assets. Alternative options to mitigate grid congestion situations are battery storage systems and DSM (Müller et al., 2015).

Whereas grid reinforcements seem to be a straight forward approach, they cause additional investments and lead to a reduced average asset utilization. Components, such as lines and transformers, are being oversized for most of the grid load situations. As a consequence, this leads to an unfavorable economic efficiency. In contrast, DSM measures can be applied using existing components, like electric HP and EV, which could be an economic advantage (Arteconi et al., 2016). However, for situations of high electric loads caused by concurrent usage of electric HP and EV charging, additional local generation capacity provided by distributed CG might be a suitable alternative or support technology (Schumacher et al., 2015).

To analyze the congestion mitigation potential of different CG designs the CIGRE reference distribution grid is considered. It represents a typical setup of a suburban DS and originally consists of 120 SFH distributed over six feeders (Dickert et al., 2013). In contrast to the SFH setup, in this thesis the design focus is on CG systems installed in MFH. Therefore, some corrections in the grid structure are necessary to incorporate a suitable number of MFH while maintaining the specific electric load on grid assets. A detailed description and schematic of the DS model can be found in section 3.2.2. Using the above reference grid model, a PFC can be conducted. In comparison to the NES, this PFC explicitly considers grid limitations. The result of the PFC comprises various DS state variables, such as voltages, currents and relative asset utilization within the network. Grid congestions are identified based on these state variables, using an approach developed by Schlösser (2019). As a result, the demand for congestion power P_{cong} to restore a reliable operation of the grid can be determined.

In figure 2.6 a grid congestion is shown for an exemplary scenario. Within the considered grid 50 % of the SFH are equipped with a PV panel and an electric HP. Additionally, 50 % of the vehicles within the district are assumed to be electric. In the depicted graph negative values for P_c indicate a need for either a load reduction or an increased local generation. During the course of the considered day there is a rather constant power demand due to heating. A comparably low power generation from PV panels in the morning can be observed that already decreases in the afternoon. At that time a majority of occupants arrives at their homes leading to an increased usage of household appliances and EV charging. This concurrent load increase cannot be covered by local generation and leads to a grid overload which is quantified by the negative congestion power.

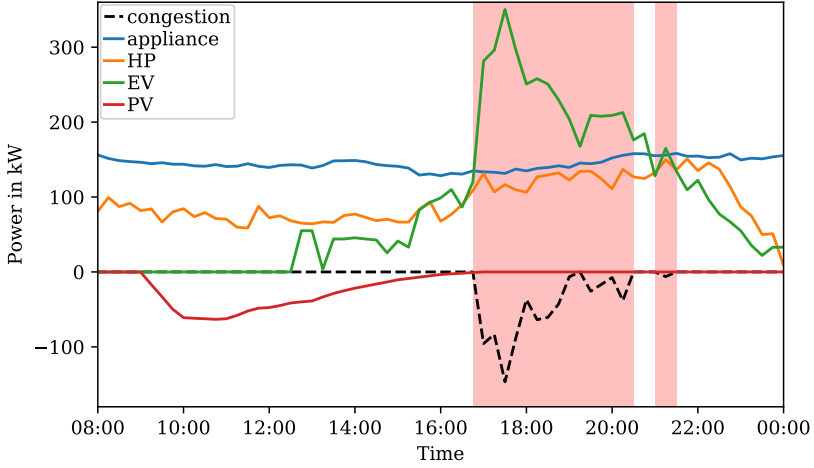


Figure 2.6: Exemplary load situation of an LV grid in January. The combination of all loads and the lack of PV injection leads to a congestion during evening hours.

During the highlighted phase CG systems could be activated to reduce or even eliminate the grid congestion. Hence, to enable the provision of negative congestion power, the information on the DS state needs to be forwarded to the CG systems. In contrast to the depicted grid congestion, positive values occur in situations where the power injection by distributed generation, especially PV systems, is stressing the grid. In those cases a reduced power generation of CG systems is beneficial.

2.2 Cogeneration in a dynamic grid context

When analyzing BES in a dynamic grid context an important step is how to integrate the dynamic grid state into the design and operation. In addition, the technical setup describing the components of a BES and its performance assessment is of major importance. This section first gives an overview of the considered CG system and its performance assessment. Afterwards, details on the state integration of the NES and DS is explained. Based on the results of the power system state calculation presented in section 2.1 the conversion into state signals that are compatible with the CG control scheme will be introduced. This part is followed by the actual integration of the power system state signals into the CG's controls. It emphasizes the conversion of state signals into controller set points. To conclude this section an example of a typical flexibility provisioning situation is shown.

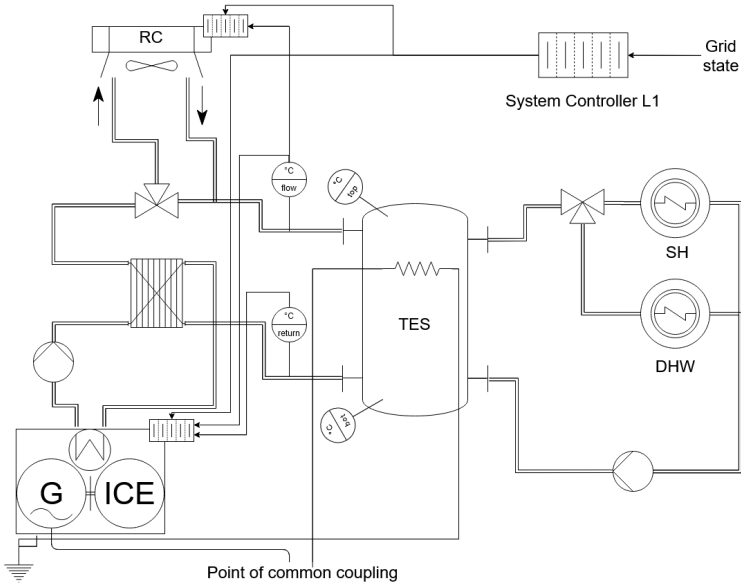


Figure 2.7: Piping and instrumentation diagram of the considered CG system. It comprises generators, sinks, a storage tank and the two level control scheme.

2.2.1 Cogeneration system

In contrast to traditional distributed CG systems for residential buildings the system considered in this thesis is a monovalent one. It is designed to reliably supply the thermal demand of a small to medium size MFH without the need for a peak load gas boiler as used in conventional systems. Nevertheless, an additional electric heating rod (HR) installed in the TES is available to support the CG device to cover the peak thermal demand of the corresponding building.

An overview of the CG system is given in figure 2.7. The system comprises the CG device itself, which is used to heat the TES. Thermal demand arising from space heating (SH) and domestic hot water (DHW) is provided via heat exchangers installed in the TES. Thus, a decoupling of the heat distribution circuits from the heat generation is achieved. The hydraulic decoupling in combination with the storage capacity of the TES provides operational flexibility for the CG device. Further, the TES contains the aforementioned HR to heat the top layers. This way the heat supply of a building is ensured even if the thermal load temporary exceeds the heating power of the CG unit.

The control concept of the system consists of two layers. A two point TES controller (level-1) supervises the temperature of different storage layers. Besides, it coordinates different sub-controllers depending on the grid state. Additionally, a downstream PID controller (level-0) sets the CG's thermal and electrical output. Details on the grid-integrated control concept will be presented in section 2.2.3.

In contrast to ordinary CG systems, the ones that are analyzed in this work are equipped with an optional re-cooling (RC) device. The purpose of this device is to dump excess thermal energy in situations where the power generation is very valuable but the TES is fully charged. This way, the operation of the CG unit and its power supply to the grid is entirely independent of the thermal energy demand of the building. Hence, the device is turned into a fully controllable grid asset comparable to a conventional power plant. Practical examples of the RC utilization are phases of grid congestion or a high CO₂ intensity of grid power in combination with a high power price.

2.2.2 Performance assessment

To assess the enviroeconomic performance of CG systems a comparison to a reference supply system is necessary (de Paepe et al., 2006). For this purpose, a condensing gas boiler (GB) to supply the SH and DHW demand is assumed. Today, it still is the standard technology in most MFH (Deutsche Energie-Agentur GmbH, 2018). Furthermore, the components used for DHW preparation and heat emission within the building are compatible regarding flow temperature requirements for boilers and CG systems. Thereby, it ensures a fair and reasonable comparison. To buffer peak heat demand the reference system is equipped with a TES as well.

The evaluation of the CG's competitiveness in reducing emissions at low cost is done by applying the commonly used measure of CO₂ abatement cost, as used by Patteeuw et al. (2015). In the following, the definition of this measure is presented. Herein, an annualized NPV method is used (Breuer, 2012). It is defined as the difference of the annual supply cost divided by the CO₂ abatement as stated in equation 2.2.

$$AC_{\text{CO}_2, \text{CG}} = \frac{\Delta C}{\Delta m_{\text{CO}_2}} = \frac{AF(i, \tau) \cdot (I_{\text{CG}} - I_{\text{GB}}) + OPEX_{\text{CG}} - OPEX_{\text{GB}}}{m_{\text{CO}_2, \text{GB}} - m_{\text{CO}_2, \text{CG}}} \quad (2.2)$$

The annuity factor used in the definition of the CO₂ abatement cost is calculated according to equation 2.3 using a typical duration of $T = 20$ a for heating system investments. Further, an adequate target rate of $i = 3$ % p.a. is assumed considering a mixture of equity and debt capital for commercial investors (Deutsche Energie-Agentur GmbH, 2019).

$$AF(i, T) = \frac{(1+i)^\tau \cdot i}{(1+i)^\tau - 1} \quad (2.3)$$

In the following the difference in annual supply cost, which can be found in the nominator of 2.2 is explained in detail. The first part of the annual supply costs arises from capital expenses (CAPEX) due to the initial investment into the system (2.4). Since the considered CG system comes with an electric HR and is optionally equipped with a re-cooling system, these components are accounted for as well.

$$I_h = I_{\text{ECS}} + I_{\text{TES}} + \underbrace{I_{\text{HR}} + I_{\text{RC}}}_{=0, \text{ for } h=\text{GB}} \quad (2.4)$$

The operational expenses (OPEX) in equation 2.5 are formed by four main elements and reveal specific differences between a CG system and the reference one. Herein, the first three elements are the expenses for gas consumption, CO₂ allowance certificates and cost for system maintenance. A counterpart to these cost elements are the payments for net electricity export to the grid which is generated by CG systems.

$$\begin{aligned} OPEX_h &= E_g(t) \cdot p_g(t) + m_{\text{CO}_2} \cdot p_{\text{CO}_2} + EX_{\text{m},h} + \int P_{\text{el}}(t) \cdot p_{\text{el}}(t) dt \\ &= E_g(t) \cdot (p_g(t) + f_{\text{CO}_2,g} \cdot p_{\text{CO}_2}) + EX_{\text{m},h} + \underbrace{\int P_{\text{el}}(t) \cdot p_{\text{el}}(t) dt}_{=0, \text{ for } h=\text{GB}} \end{aligned} \quad (2.5)$$

Especially expenses for maintenance need to be distinguished according to the underlying technology. For the GB the wearout is rather independent of the hours of operation and mostly determined by its thermal capacity. Therefore, maintenance expenses are often expressed as multiples of the initial investment following equation 2.6.

$$EX_{\text{m},h} = \begin{cases} I_h \cdot 0.03 & , h=\text{GB} \\ W_{\text{el},h} \cdot p_{\text{m},h} + p_{\text{rev},h} \cdot n_{\text{rev}} & , h=\text{CG} \end{cases} \quad (2.6)$$

In contrast to that, the CG system's wear not only depends on its capacity, but also on its actual utilization. The combination of both is expressed by the produced electricity $W_{\text{el},h}$ and a corresponding price $p_{\text{m},h}$. Additionally, CG systems require occasional engine revisions even before they reach the expected service life. The number of required revisions, however, depends on the operational conditions as well and is mainly influenced by the cycling frequency. Details on the calculation of $p_{\text{m},h}$ and $p_{\text{rev},h}$ are presented in section 3.4.1.

Considering the aforementioned effects, the expected number of engine revisions is calculated following equations 2.7 to 2.8.

$$n_{\text{rev}} = T \cdot \frac{t_o}{t_{\text{rev}}} \quad (2.7)$$

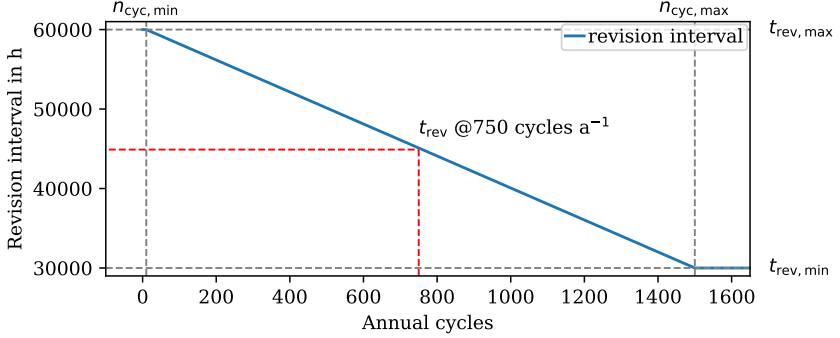


Figure 2.8: Revision interval of a CG unit depending on the annual number of cycles.

$$t_{\text{rev}} = \max\left\{\min\left(t_{\text{rev,max}}, \frac{t_{\text{rev,max}} - t_{\text{rev,min}}}{n_{\text{cyc,min}} - n_{\text{cyc,max}}} \cdot n_{\text{cyc}} + t_{\text{rev,min}}\right), t_{\text{rev,min}}\right\} \quad (2.8)$$

Figure 2.8 shows the revision intervals defined by equation 2.8 over the annual number of cycles. The example depicted in red shows the revision interval to be 45.000 h based on a cycling frequency of 750 a⁻¹. In practical terms, this roughly corresponds to two cycles per day. Using a traditional sizing approach it would require a major engine revision after approximately nine years of usage. The limiting values of the curve t_{rev} and n_{cyc} are based on empirical data and are subject to uncertainty. The actual revision intervals depend on a variety of external factors beyond cycling behavior. Nevertheless, the approach chosen holds as a reasonable assumption (Dressler, 2016)(Mühlstein, 2014)(ASUE e.V., 2011).

In contrast to a GB, a CG system produces power that can either be used on the directly premises or fed to the power grid. Since the aim of this thesis is a technology assessment, a feed into the grid and a rating according to the wholesale power price is taken as a basis. Only by following this approach a distinct view on the social cost of utilizing CG for CO₂ abatement purposes is possible.

The second important part of the CO₂ abatement cost is the actual emission reduction that can be achieved using CG technology. To enable the calculation of this figure, first, the actual CO₂ emission needs to be defined as follows:

$$m_{\text{CO}_2,\text{h}} = E_{\text{g,h}} \cdot f_{\text{CO}_2,\text{g}} - \underbrace{\int P_{\text{el,h}}(t) \cdot f_{\text{CO}_2,\text{el}}(t) dt}_{=0, \text{ for h=GB}} \quad (2.9)$$

Based on 2.9 the emission reduction Δm_{CO_2} can be calculated according to equation 2.10. Detailed information on assumptions and input data for the assessment are given in sections 3.3, 3.4 and 3.5.

$$\Delta m_{\text{CO}_2} = f_{\text{CO}_2, \text{g}} \cdot (E_{\text{g}, \text{GB}} - E_{\text{g}, \text{CG}}) + \int P_{\text{el}, \text{CG}}(t) \cdot f_{\text{CO}_2, \text{el}}(t) dt \quad (2.10)$$

The above explained assessment towards CO_2 abatement cost only reflects the NES perspective. Therefore, an evaluation with respect to the system's influence onto the local DS must be considered as well. In that sense, the previously presented congestion power demand P_c within a DS plays an important role. As a matter of fact, its mitigation is one of the targets that the optimization strives for. The relative residual congestion energy demand of a particular DS where a CG device is placed serves as a further performance indicator. It is calculated according to the following equation and considers the DS part that is downstream to the transformer.

$$\bar{w}_{c, \text{res}} = \frac{W_c}{W_{c, \text{ref}}} \quad (2.11)$$

Within this relative residual congestion energy demand the absolute annual congestion energy is defined as follows:

$$W_c = \int (P_{c, \text{dem}}(t) - P_{c, \text{sup}}(t)) dt \quad (2.12)$$

The congestion power demand is the result of the PFC for the considered DS using the reference case (cf. 2.1.2). It constitutes the power change that is necessary to restore a safe network operation. Besides, equation 2.13 defines the congestion power supplied by the CG which corresponds to the minimum value of the current congestion power demand $P_{c, \text{dem}}(t)$ and the electrical capacity of the CG unit $P_{\text{el}, \text{CG}}(t)$. Thus, excess or insufficient power supply of the CG device is not rewarded in the calculus.

$$P_{c, \text{sup}}(t) = \min\{P_{\text{el}, \text{CG}}(t), P_{c, \text{dem}}(t)\} \quad (2.13)$$

2.2.3 Cogeneration control concept

The CG system considered in this thesis not only ensures a reliable heat supply of a building, but needs to operate in a grid-driven manner as well. To invoke the desired operation a state of the surrounding energy systems is passed to the CG controls via a grid control signal. In

this section the mechanisms on how the grid control signal is transferred to actual operation of the CG system is presented.

In general, applications such as DSM or VPP use direct or indirect control approaches. Direct control is able to manipulate the operational behavior, like switching events and output modulation, directly in the device controls. In contrast, indirect approaches make use of specific signal to provide an incentive for a desired control action. An example for a direct scheme is the VHPready standard that is used to coordinate VPP (Baumann et al., 2015), (Sauer and Prus, 2015). The reliability of this standard needs to be comparably high, since it is used to integrate a VPP in the power market (Walter, 2016). However, the requirements regarding modulation ramps and the direct access onto the device controls limit the applicability of a direct control with off-the-shelf technologies (Maaß, 2012). Regarding indirect approaches, dynamic tariffs are a common implementation.

Due to the priority of covering a building's heat demand and the wide range of different proprietary control systems an indirect control approach was chosen to set the operational status of the CG device in this analysis. The approach is based on the SGready concept for heat pumps, where an ordinary control scheme comprising a two point TES controller (level-1) and a PID controller (level-0) to modulate the device's thermal and electrical output is used (BWP, 2013). Where standard heat-driven CG systems have constant threshold temperatures implemented in the TES controller, the considered grid-driven control scheme uses variable thresholds. By dynamically setting these thresholds a relative pre-conditioning of the TES can be achieved. As a consequence, the available operational flexibility of a CG system can be influenced in a grid-supportive way. The dynamic threshold temperature is used to activate the CG device on demand.

Figure 2.9 shows a schematic chart of the indirect grid-driven control concept. It shows the bottom and top temperature of a TES for three different grid states. These states are indicated by the grid control signal $\{-1, 0, 1\}$ in the upper part of the figure. In the first phase the grid control signal does not imply a need for specific device operation. Therefore, the CG system stays in its ordinary heat-driven operation in which it is turned on as soon as the top temperature of the TES passes the $T_{\text{TES,nom}}$ threshold from above. Within this mode the CG device stays in operation until the bottom temperature hits $T_{\text{TES,nom}}$ from below. Here, the TES reaches its desired state of charge.

Following the same control principal, the operation phase of the CG system can either be extended or reduced. Furthermore, by dynamically changing the threshold levels in accordance with the grid control signal the device can be turned on or shut down. For the analysis of CG devices the nominal TES temperature was assumed to be $T_{\text{TES,nom}} = 60^\circ\text{C}$. To ensure the preparation of DHW on the one hand, and keep the heat system's fluid from boiling on the other hand, the minimum and maximum threshold temperatures were set to $T_{\text{TES,min}} = 50^\circ\text{C}$ and $T_{\text{TES,max}} = 90^\circ\text{C}$ respectively.

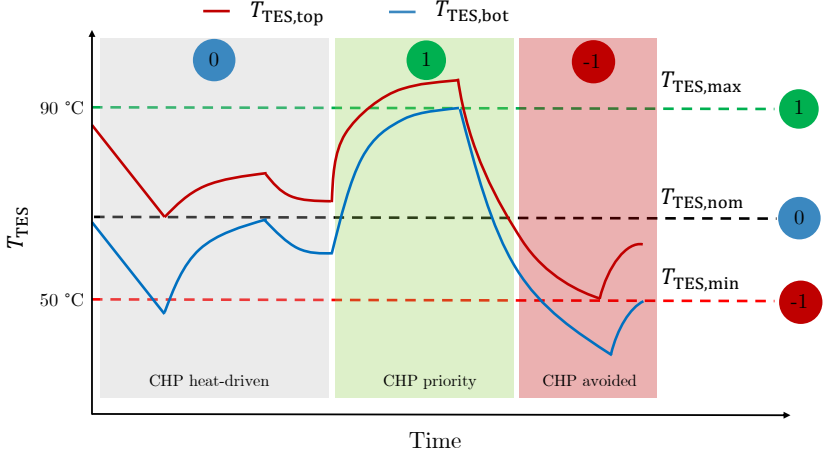


Figure 2.9: Implementation of the considered CG operation modes. Three available modes lead to different set temperature levels within the TES.

2.2.4 Grid state signals

The potential for congestion mitigation and low CO_2 abatement cost can be enabled by taking the additional investment into a CG system rather than a standard GB system. To justify this additional investment, however, the abatement of CO_2 emissions and eventually a reduction in operational expenses need to be achieved. Whereas the investment into a CG system is already fixed with the system sizing, the operational expenses can still be influenced within the expected life of the device 2.2.3.

The power system state information that is passed to the CG system distinguishes the NES and DS. The DS's state is expressed using the congestion power demand. A negative congestion power demand indicates the need for increased power injection, whereas positive values require an electrical output reduction. In addition to an output reduction the utilization of the electric HR is possible to mitigate congestions. An example situation is a transformer overload during reverse power flow.

For the purpose of device operation a qualitative indication of the DS state is used instead of the actual congestion power demand. When passing this signal to the CG device the quantitative information on the degree of a congestion is lost. Nevertheless, the pure information on whether the grid is congested or not is sufficient for the device itself. In a practical im-

plementation of this scheme the number of participating devices in a grid, and thereby the aggregated provisioning of grid flexibility, can vary. Additionally, the realization of an actual swarm of grid-driven distributed generators needs some sort of aggregation and coordination facility. In contrast to the individual device the quantitative information on the DS state would be inevitable for this aggregator (Raab et al., 2011)(Palizban et al., 2014)(Ruiz et al., 2009).

In comparison to the DS state signal, the state information of the NES is more sophisticated. As explained in section 2.1 the current generation mix can be expressed using a price and CO₂ intensity. Looking separately at both indicators, however, an opposite correlation can be recognized at many times. Especially within a marginal grid state approach phases of low power prices often come with high CO₂ intensities. Therefore, the usage of only one indicator would not be sufficient. Instead, these two indicators are combined in the sense of environmental economics. A dynamic enviroeconomic value $\pi(t)$ can be calculated following equations 2.14 and 2.15. Herein, the time-variant CO₂ intensity $f_{\text{CO}_2, \text{el}}(t)$ and power price $p_{\text{el}}(t)$ are used in relation to their corresponding annual maximum values $f_{\text{CO}_2, \text{el}, \text{max}}$ and $p_{\text{el}, \text{max}}$. Hence, a multiplicative expression of a time-variant enviroeconomic value of power is obtained. In addition, equation 2.15 normalizes the absolute value of $\pi_{\text{abs}}(t)$ using its annual maximum value $\pi_{\text{abs}, \text{max}}$.

$$\pi_{\text{abs}}(t) = \frac{f_{\text{CO}_2, \text{el}}(t)}{f_{\text{CO}_2, \text{el}, \text{max}}} \cdot \frac{p_{\text{el}}(t)}{p_{\text{el}, \text{max}}} \quad (2.14)$$

$$\pi(t) = \frac{\pi_{\text{abs}}(t)}{\pi_{\text{abs}, \text{max}}} \quad (2.15)$$

Like the price trend and the CO₂ intensity curve, the resulting enviroeconomic value shows a repetitive pattern. This pattern holds the potential to be exploited using a flexible BES that operates preferably during peak phases. Even when using a rule-based controller the dynamic enviroeconomic value of power can be addressed. For this purpose, a variable threshold that depends on the moving maximum and minimum of the enviroeconomic value is implemented. This variable threshold is declared by the following equation introducing the design parameter λ_{force} that affects the HVAC controls.

$$\pi_{\text{force}}(t) = (\pi_{\text{max}}(t) - \pi_{\text{min}}(t)) \cdot \lambda_{\text{force}} + \pi_{\text{min}}(t) \quad (2.16)$$

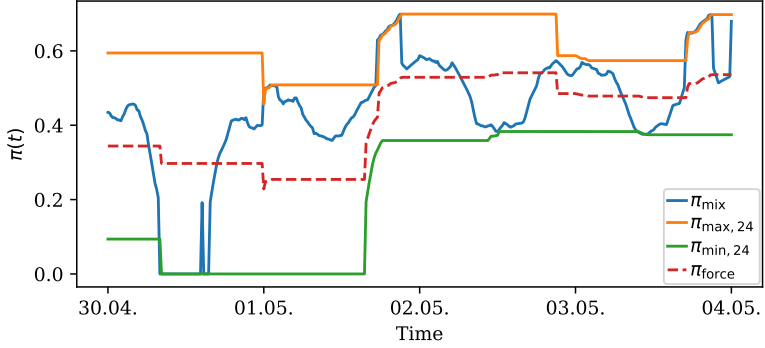


Figure 2.10: Example curve for the relative enviroeconomic value of power $\pi(t)$ with its corresponding 24 h minimum and maximum values. Combined with a relative threshold of $\lambda_{\text{force}} = 0.5$ it leads to a forced operation above $\pi_{\text{force}}(t)$.

Using the above explained approach, the regular repetition of the signal is being considered, enabling an approximate identification of the most valuable operation phases. An exemplary curve for the relative enviroeconomic value is depicted in figure 2.10.

In addition to the actual signal a moving minimum and maximum within the considered forecast horizon is depicted. This prediction horizon can be set between 0 and 48 hours depending on the design and purpose of the CG system. Lower frequency patterns that show periods above 48 hours exist as well. Especially an annual frequency in the enviroeconomic value of power can be identified. Very low frequencies, however, could only be harnessed by installing exceptionally large seasonal TES (Makarov et al., 2012). These storage concepts are not in the scope of this thesis.

The duration of an optimal operation phase is not only determined by the dynamic enviroeconomic value. As a matter of fact, the operational flexibility of the BES during that phase plays a crucial role. It largely depends on CG system design in relation to the thermal demand curve of the building (Stinner, 2017). To account for these different average operational flexibility levels, the aforementioned adaptive threshold is considered as a further design parameter of the CG system within the optimization.

Besides the identification of time windows where the operation is favorable according to the NES, it is also necessary to avoid phases where no CO₂ abatement is possible. The applicable threshold for these situations can be defined by comparing the emission-wise performance of a specific CG system against the reference boiler setup. According to equation 2.17 the marginal CO₂ emission reduction associated to thermal energy supply can be calculated.

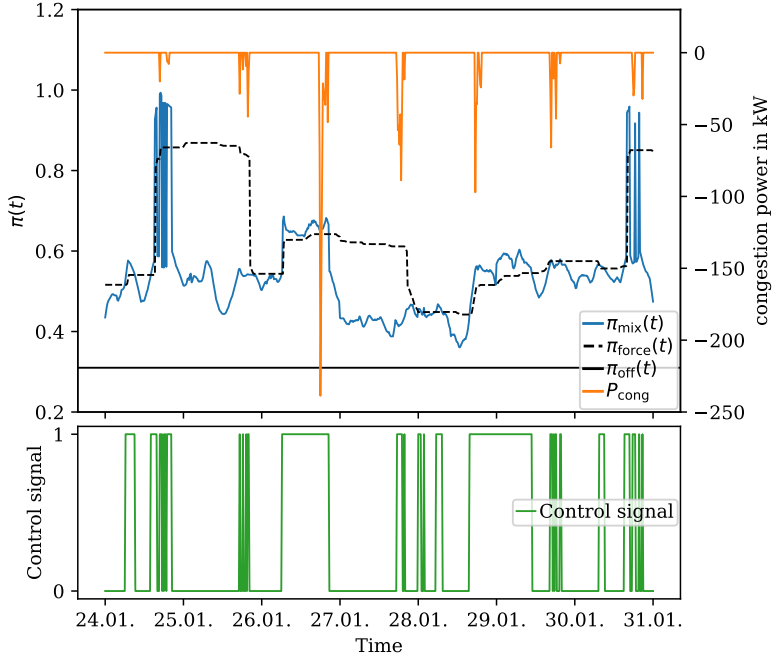


Figure 2.11: CG operation based on enviroeconomic value $\pi(t)$ with a corresponding threshold $\pi_{\text{force}}(t)$ and demand for congestion power in the 2017 reference scenario.

$$\frac{\Delta m_{\text{CO}_2}(t)}{\Delta Q_{\text{th}}} = \frac{m_{\text{CO}_2, \text{GB}}(t) - m_{\text{CO}_2, \text{CG}}(t)}{\Delta Q_{\text{th}}} = \frac{f_{\text{CO}_2, \text{g}}}{\eta_{\text{th, GB}}} - \left(\frac{f_{\text{CO}_2, \text{g}}}{\eta_{\text{th, CG}}} - f_{\text{CO}_2, \text{el}}(t) \cdot \sigma \right) \quad (2.17)$$

Since the optimization target is to achieve low CO_2 abatement cost, the monetary benefit of operation needs to be taken into account as well. Therefore, the marginal cost reduction for thermal demand supply are considered by equation 2.18.

$$\frac{\Delta \text{OPEX}(t)}{\Delta Q_{\text{th}}} = \frac{\text{OPEX}_{\text{GB}}(t) - \text{OPEX}_{\text{CG}}(t)}{\Delta Q_{\text{th}}} = \frac{p_{\text{g}}}{\eta_{\text{th, GB}}} - \left(\frac{p_{\text{g}}}{\eta_{\text{th, CG}}} - p_{\text{el}}(t) \cdot \sigma \right) \quad (2.18)$$

Where both the above equations show positive values the operation of the CG system is favorable and an operational release will be granted.

An example for a grid-driven operation of a CG system following the approach described above, can be seen in figure 2.11. The upper part shows the current energy system state. Both the relative enviroeconomic value of power and the absolute demand for congestion power can be seen. Using these indicators, favorable operation windows are present. The BES controls identifies them whenever the state signals pass their corresponding threshold values. In the example the CG system is meant to use its full positive power flexibility whenever the DS is congested or the enviroeconomic value of power is above the adaptive threshold. As a result of the energy system state, the lower part of the figure shows the control signal that is passed to the main CG system controller. This control signal is transferred to appropriate TES temperature thresholds using the method presented above.

2.3 Design optimization procedure

In the following section the optimization procedure is presented. The main goal of this thesis is to analyze the optimal design of grid-driven CG systems in a dynamic energy system context. Therefore, in the first part of this section the optimization approach that was chosen is described. The most important design variables of a CG system are identified and their general effects on the operational behavior are introduced. Afterwards, the setup of the specific GA is elaborated and the choice of different GA parameters is presented.

2.3.1 Optimal design concept

According to subsection 2.2.2 the performance of a grid-driven CG device can be assessed towards the following targets.

- CO₂ abatement cost (enviroeconomic target)
- Congestion mitigation in DS (technical target)

The combination of the above conflicting targets forms a multi-objective optimization with an n-dimensional vector as independent variable x . The objectives within this optimization are equally weighted.

$$\min_x f(x) = \min_x \{f_1(x), f_2(x)\} = \min_x \{AC_{CO_2,CG}(x), w_{c,res}(x)\} \quad (2.19)$$

To achieve a distinct optimization target as declared in equation 2.19 the vector x of most important independent variables needs to be identified. Based on this vector the actual optimization algorithm is implemented. The grid-driven CG systems considered in this thesis will be optimized to exploit a dynamic grid status signal and thereby achieve a CO₂ emission

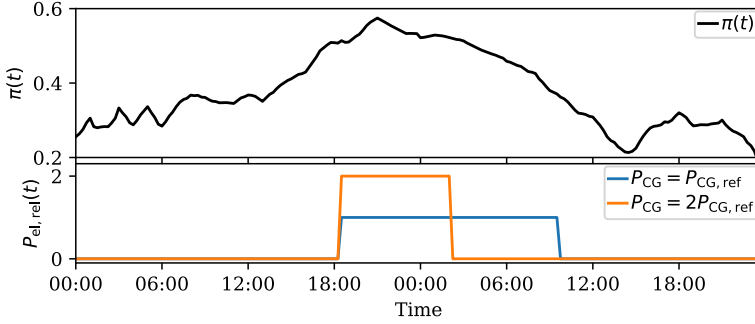


Figure 2.12: Exemplary effect of increasing electrical capacity P_{CG} on the operational assessment using the enviroeconomic value $\pi(t)$.

reduction at lowest possible cost in comparison to a reference system. Additionally, the CG system is meant to mitigate grid congestion of the local DS.

From various possible design variables the electrical capacity $P_{el,CG}$, the TES volume V_{TES} , the relative threshold λ_{force} at which the CG device switches to forced operation and the applicable forecast horizon t_{hor} of the enviroeconomic value $\pi(t)$ are chosen to form the vector of independent variables. Their general effects on the operational behavior will be briefly explained in the following.

Increasing the electrical capacity of the device $P_{el,CG}$ while keeping all other design parameters unchanged leads to decreasing time windows of each operation cycle as the TES is charged faster. Figure 2.12 exemplary shows the aforementioned effect.

In this respect, doubling the device's capacity leads to an approximately halved time window during an operation cycle. Nevertheless, the electrical and thermal energy supplied within that phase is expected to change only slightly. As a result, the CG system provides an almost equal amount of energy flexibility that is characterized by a lower temporal but a higher power flexibility. The emission-wise balance, however, shows that the larger sized CG system is better able to operate during the peak phase of the enviroeconomic value, which holds superior environmental performance in the sense of the assessment methodology presented in 2.2.2.

The operation of a CG system and its power injection into the grid would affect both prices and CO_2 intensity of a NES in practical applications. However, when putting the electrical capacity of a single distributed CG unit in comparison to the average load of the NES, this influence becomes negligible. Hence, a direct coupling with the NES is not considered and therefore the operation of the CG system has neither an effect on the current CO_2 intensity

nor on the current power price. Due to that assumption, the feed in potential of a considered CG device is not limited towards power or energy.

Besides the environmental performance, the potential for congestion management needs to be considered. For this design criterion the capacity effect on the time window holds as well. In contrast to the NES considerations above, the comparison of capacities within a DS context necessitates a different assumption. Specifically, the capacity of a CG device is in the same order of magnitude as the local electric load. As a consequence, the congestion mitigation potential with respect to time and power is limited by the congestion power demand of the grid. Hence, increasing the capacity of a CG device is only beneficial to a limited extend. As soon as the electrical capacity reaches the congestion power demand at a given point in time, a marginal capacity increase would have no further positive effect for this particular situation. Nevertheless, the exemplary analyses above holds true only for the particular period considered. In fact, a seemingly unnecessary oversizing for several time sections could be overcompensated by other phases where the demand for congestion power is higher. The presented example points out that the existence of an optimal electrical capacity can be assumed. Further, its value can be determined by applying an appropriate optimization method that covers a full year period.

A similar analysis can be done for the TES volume. However, in contrast to the device's capacity a different effect can be found as depicted in figure 2.13. Increasing the TES volume V_{TES} causes a longer operational time window for each cycle. This enables the CG device to better exploit longer phases of high enviroeconomic electricity values. In addition, the time to discharge the TES again increases as well since the thermal energy demand of the BES stays approximately the same as before. Only slight differences due higher storage losses can be expected. As a consequence, CG systems with a relatively smaller TES are operated even during phases of low power values since they reach the minimum storage temperature. Hence, the exploitation of fluctuations in the enviroeconomic value of power or the grid congestion mitigation could be worse.

An emission reduction, as well as a DS service provision, can be improved by installation of large CG devices. These, however, usually necessitate a higher investment which might overcompensate the benefit of reduced emissions. Consequently, increasing the capacity can increase the CO₂ abatement cost even though an absolute emission reduction is achieved. In fact, the aforementioned optimization goals of low CO₂ abatement cost and good congestion mitigation compromise each other. To deal with this trade-off a multi-objective optimization approach is considered. As presented before, the enviroeconomic performance of a CG system not only depends on a suitable sizing, but largely on the operation in favorable times. The operation, however, affects the optimal sizing again. Therefore, the design optimization of grid-driven CG should include both the sizing and the operational design in an integrated approach (Ooka and Komamura, 2009).

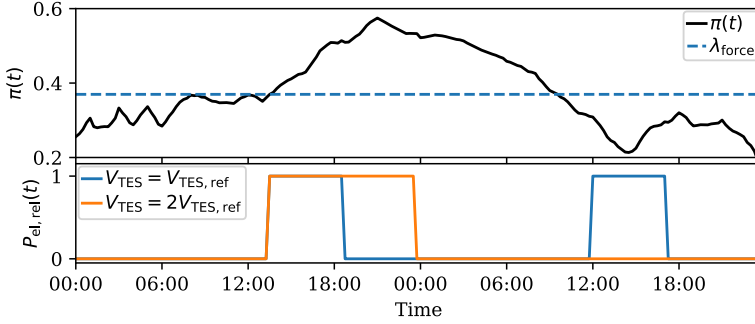


Figure 2.13: Exemplary effect of the TES volume V_{TES} on the operational assessment using the enviroeconomic value $\pi(t)$.

To comply with the demand for an integrated optimization the control design will be addressed in the following. A variable threshold λ_{force} is introduced to time the forced operation of a CG system. An example of how this design parameter affects the operation and thereby the enviroeconomic performance of the system is given in figure 2.14. A first threshold level allows for forced operation at a low enviroeconomic power value. Due to the early startup of the CG device the operational flexibility is already exhausted before π_{AC} reaches its local maximum. This way the potential for achieving low CO_2 abatement cost is only partially harnessed by the CG system.

In contrast to that, a higher threshold level λ_{force} puts the CG into forced operation at a later point, where the enviroeconomic value of power reaches its local maximum. Thus, the electric energy fed into the grid has a higher average value, which in turn leads to superior performance of the higher threshold setting in this particular situation. Of course, the advantage seen in this exemplary period might not hold at all times, which makes an entire annual assessment necessary.

Another design parameter that influences the operational performance of the considered CG systems is the forecast horizon t_{hor} that is applied to calculate the upcoming enviroeconomic value of power. In this regard, the temporal cycle flexibility of the system is important. It is defined as the time in which a BES can provide flexibility and recover again from this provision (Stinner, 2017). Depending on the available temporal cycle flexibility an optimal forecast horizon exists. For CG systems with a high thermal output and low storage capacity only a low temporal cycle flexibility can be expected. Frequent device cycling is a consequence which makes a long forecast horizon needless. Instead, a shorter forecast horizon would be beneficial that indicates favorable operation windows precisely. Vice versa, CG systems with comparably large TES volumes could be able to exploit the additional information that is

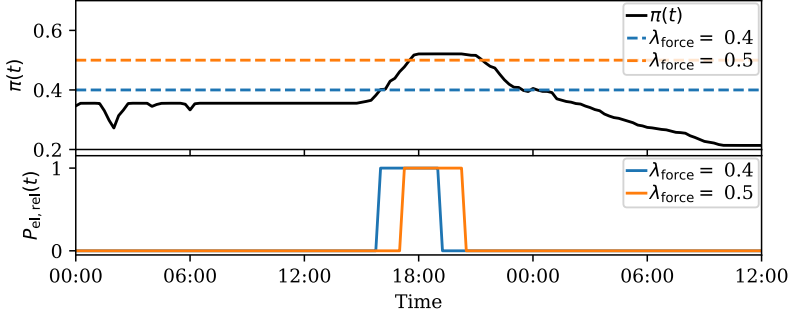


Figure 2.14: Exemplary effect of the relative threshold level λ_{force} on the operational assessment using the enviroeconomic value $\pi(t)$.

provided by a longer prediction horizon t_{hor} . Just like the other parameters before an optimal forecast horizon is expected to be found by conducting a GA.

2.3.2 Evolutionary algorithm implementation

With the independent variables identified above the considered CG system can be optimized utilizing a suitable optimization approach. In this respect, different methods were assessed towards their suitability. The methodology of this work relies on dynamic non-linear physical models. These are able to properly address non-linear effects that are of great importance when analyzing BES with respect to their operational flexibility. Such non-linear effects concern performance curves used in the system models, e.g. electrical efficiency of the CG device.

A study by Milan et al. (2015) proposes a method to incorporate non-linear part-load efficiency curves of CG systems using MILP. However, the added value depends very much on the considered operation scenario. In case of dynamic CG operation schemes the influence of part-load efficiencies is significant. A major downside of the presented linearization approaches is the computational burden, leading to 20 to 10.000 times the calculation time for MILP models.

Besides efficiency curves the realistic modeling of fluid temperatures within the BES is most critical. In this respect, the return temperature of the heating fluid that flows into the lower layers of the TES determines its temperature stratification. As consequence, the temperature distribution of the TES and thereby the usable storage capacity strictly depends on the return temperature which itself is determined by the current thermal load situation of building. Higher thermal loads due to low ambient temperatures lead to an increased mass flow in the heat emission system. Lower exposure times of the heating fluid within radiators or other

heat exchangers consequently result in higher return temperatures. For that reason, linear modeling approaches such as MILP are not well suited to deal with the optimization problem at hand (Pruitt et al., 2013)(Ooka and Komamura, 2009).

Further, the application of a MINLP approach using the Modelica based Optimica package was found to be not suitable, due to the high complexity and operational dynamics of the considered CG system. Especially the use of hybrid models induced by the integration of the CG control concepts as presented in section 2.2.3 has proven to be incompatible for the usage within a MINLP (Åkesson et al., 2010).

Regarding heuristic optimization approaches the concept of evolutionary algorithms (EA) are considered to solve the present optimization problem. According to (Simon, 2013) the definition of an EA strongly depends on its context. In different works the term EA is used to refer to computer intelligence, while others use it to describe machine learning. However, in this work an EA refers to a population based meta-heuristic optimization.

When using dynamic physical modeling methods to analyze and optimize BES the application of EA generally has some advantages. Caldas and Norford (2003) found EA to be very effective in solving complex optimization problems that cannot be easily tackled using explicit optimization approaches. Further, the application of EA allows the coupling of the optimization algorithm itself with various simulation environments without the need for model simplification. In general, the aforementioned features prove an EA to be a valid approach to solve the multi-objective optimization problem considered in this work. From the range of different EA implementations the GA was chosen and will be presented in the following.

The general workflow of a GA is depicted in figure 2.15, where the initialization of a population marks the beginning of an algorithm. Each individual carries the information of the optimization problem and is thus defined in the problem space. The problem space itself is the set of possible design parameter values for the given problem, hence representing all possible parameter combinations. In analogy to genetics the stored information is called genes and is saved in the individual as a list of values.

To evaluate and compare individuals several algorithms are applied on a population. These are also inspired by genetic processes and are called selection, mating, mutation and evaluation. The first three algorithms compare the individuals of the population to each other and create new individuals based on their genetic information. The manipulative algorithms are followed by an evaluation algorithm that assigns fitness values to each individual. Since the evaluation is done for every single individual in each generation the complexity of the evaluation function needs to be considered carefully to limit the computational effort to a reasonable amount. As a result of the evaluation, the fitness values indicate the individuals' performance with respect to the optimization problem's objective. Thus, they are defined in the objective space. The aforementioned algorithms are applied to the parent population in each generation creating a child population with each iteration. The parent population is then replaced by

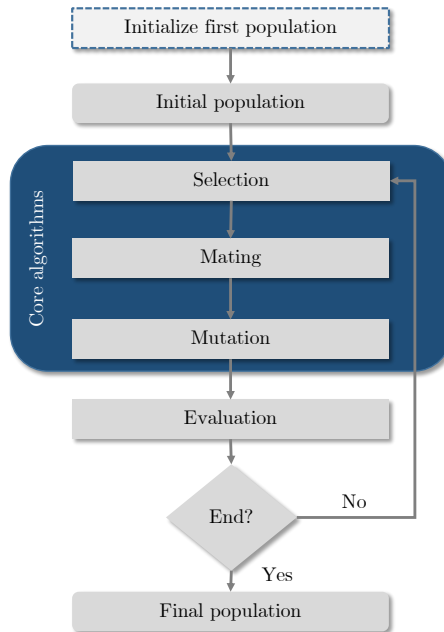


Figure 2.15: Individual steps of the GA implementation emphasizing the core algorithms.

the child population. This process is repeated until an abortion criterion is fulfilled. Details on the computational implementation of the selection and mating algorithm is presented in the following.

Herein, the choice of the selection algorithm to be applied is crucial for the performance of the GA. The algorithm draws a set of individuals from the parent population to form a mating pool. This selection can be done following different ways depending on the optimization problem at hand. In this work the "Non-dominated Sorting Genetic Algorithm II" (NSGA-II) and the "Strength Pareto Evolutionary Algorithm 2" (SPEA2) were considered. Both algorithms make use of the Pareto optimality concept which is used to deal with multiple optimization goals at the same time (Deb et al., 2002)(Zitzler et al., 2001).

The NSGA-II is a modified version of the NSGA which assigns cost to each individual in a population based on how dominant it is. Considering these cost, a population can be sorted into different levels of non-domination where the level with the least cost forms the Pareto front (Srinivas and Deb, 1994). With the NSGA-II modification this approach is further extended by taking into account the individuals that a particular individual dominates. Further, for each individual in a population the crowding distance is calculated. In that sense, individuals

with a higher crowding distance are preferred over those located in a crowded region of the result space. The cost and crowding distance values are further used to select individuals for recombination. Less-dominated individuals from sparse regions of the result space have a higher chance of being selected due to their relatively higher cost value. The concept of elitism which prevents the algorithm from dismissing superior individuals is implemented in the NSGA-II as well (Deb et al., 2002).

The SPEA2 is an improved version of the SPEA that in contrast to NSGA implements the concept of elitism explicitly by using an archive (Zitzler and Thiele, 1999). In that sense, all non-dominated individuals that are identified during an EA are stored in an external archive. Furthermore, the algorithm allocates a strength value to each individual based on how many other individuals in the population it dominates. In addition, for the dominated individuals that do not belong to the archive a raw cost value is calculated based on the strength of other individuals. It indicates the performance of an individual in comparison to the best individuals of the archive and most recent population. A further improvement of the SPEA2 is the consideration of the individual density in the result space as already seen for the NSGA-II. The modified cost are obtained by combining the raw cost and density values and determine the probability for selecting a particular individual for recombination (Simon, 2013)(Zitzler et al., 2001).

With respect to solving the multi-objective optimization problem considered in this thesis, a comparison of the NSGA-II and the SPEA2 shows similar performance. However, for a test implementation of both algorithms the SPEA2 was found to achieve a broader distribution of individuals in the final Pareto front. For that reason the SPEA2 is chosen as selection algorithm in this work.

After applying the selection algorithm a preliminary mating pool with individuals for recombination exists. Since not all previously selected individuals get to recombine, a further reduction of the pool size is necessary. For that purpose, some individuals are chosen to be part of the final mating pool by applying the cross probability ϕ_{CX} . To obtain a child population the members of the final mating pool need to recombine in a next step following a particular mating approach. Often a uniform crossover is used in which two random individuals drawn from the mating pool to exchange their genes at random points. Figure 2.16 shows a single recombination process using uniform crossover.

The left part contains the two parent individuals that were selected for recombination with their particular features (i.e. independent variables). Along each feature both individuals exchange their values with a probability of $\frac{1}{n_{par}}$. This way, an expected value of one feature flip per recombination is achieved. Nevertheless, as presented in figure 2.16 the actual number of feature flips can differ.

In this thesis a more sophisticated recombination method following Galán et al. (2013) is used. According to that, the mating pool is first sorted in descending order, either towards

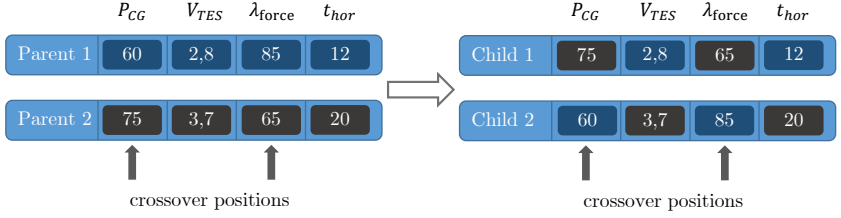


Figure 2.16: Uniform crossover approach for real-coded individuals.

the individuals' fitness or similarity. Based on the sorted mating pool, the best performing individual, which is found at the top of the list, forms the first parent in each recombination. The second parent can be chosen using either the *best-first*, *best-last* or *self-adapting* mating strategy. Depending on the optimization problem at hand, the performance of the aforementioned strategies can differ significantly. Whereas the exploitative *best-first* strategy is best suited for unimodal problems the explorative *best-last* method is better used with multimodal problems. According to Galán et al. (2013) a *self-adapting* strategy produces robust results with both problem types.

In that sense, the optimization performance of the above strategy were compared to each other. A suitable metric for the comparison of two Pareto front approximations resulting from an optimization is the reference-point hypervolume. It quantifies how good these approximations are relative to each other. Suppose the considered GA has found N points of an approximate Pareto front $F = \{\epsilon(x_j)\}$ for $j \in [1, N]$, where $\epsilon(x_j)$ is the k -dimensional evaluation function of the optimization problem. In that case, first a reference vector $r = [r_1, \dots, r_k]$, where

$$r_i > \max_j [\max_{x \in F} \epsilon_i(x)] \quad (2.20)$$

is computed. Afterwards a hypervolume with respect to the reference point can be found:

$$H(F) = \bigcup_{j=1}^N \prod_{i=1}^k (r_i - \epsilon_i(x_j)) \quad (2.21)$$

A graphical example of a two-dimensional reference-point hypervolume (i.e. hyperplane) is shown in figure 2.17. Beyond that, the Pareto front's grade is considered, which adds better comparability of particular GA implementations. The grade addresses the evolution of the Pareto front over the generations by referring each generation to the hypervolume of the final generation. This final generation is defined by the GA reaching the termination criterion and

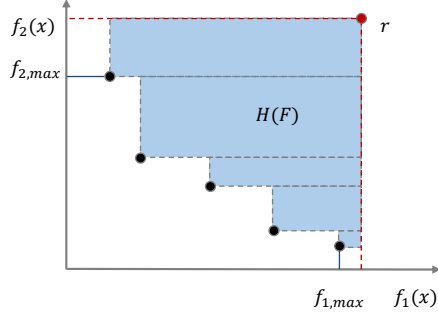


Figure 2.17: Example of a two-dimensional hypervolume indicator (hyperplane).

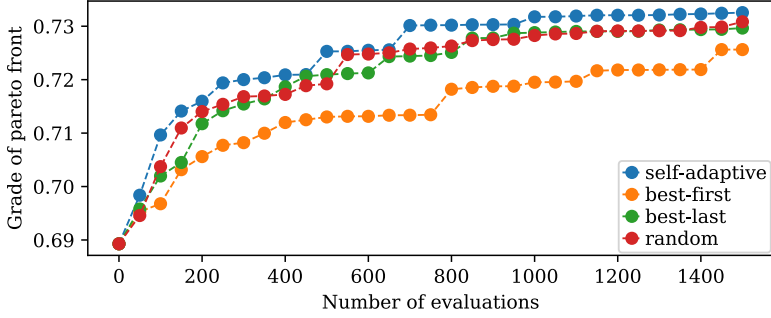


Figure 2.18: Comparison of different mating strategies using the grade of the Pareto front after each algorithm evaluation.

is therefore assumed to be the best solution that can be obtained using the GA. With these hypervolumes the evolutionary grade of a particular generation $g \in \{0, \dots, n_g\}$ is defined as

$$G_g = \frac{H_g}{H_{n_g}} \quad (2.22)$$

In the following, the grade metric is applied to compare the aforementioned mating strategies. For that purpose, each of them is tested by conducting 50 optimization runs of a single exemplary optimization case using the same GA settings. The results of this test are presented in figure 2.18.

It can be noted, that the comparison found the similarity-based *self-adapting* strategy to perform best. In this strategy the first parent is still formed by the best individual, i.e. the

top individual from the sorted mating pool. The second parent however is not statically chosen but adaptive. In the early generations of the GA the second parent corresponds to individuals from the lower part of the sorted mating pool. This makes the strategy behave rather like a *best-last* algorithm at the beginning of the EA. At that stage, the recombination goal is biased towards exploration by combining individuals that differ largely. With a converging EA in later generations the second individual is rather chosen from the top of the sorted mating pool. Here, the strategy tends to behave in a *best-first* manner to incorporate a shift towards an exploitation bias. The individuals that mate each other in that later phase of the GA are rather similar. Nevertheless, they still achieve small fitness improvements converging towards Pareto-optimality.

Since population sizes in GA are usually rather small, inbreeding can become an issue. In fact, it leads the algorithm into evolutionary dead ends in which no further improvement of the optimization result can be achieved. Therefore, mutation can be used as a final modification to the population in a GA. Thus, new information is injected. Just like the crossover explained above, a mutation occurs with a certain probability ϕ_{MT} . Different approaches of implementing mutation exist depending on the type of GA.

For the continuous GA considered in this work a uniform mutation that is centered in the middle of the search domain is chosen. After the mating strategy has formed two new individuals by applying a crossover (cf. figure 2.16) an additional mutation can occur to each feature of an individual. In that sense, the mutation algorithm goes through the features of an individual and re-initializes this feature with a chance of $\frac{\phi_{MT}}{n_{par}}$. The new values are drawn from a predefined search domain for this specific feature.

Having applied mutation, a new child population is obtained. This step concludes the core algorithm of a GA. It starts the evaluation of the child population. The above described process is iterated until the chosen stopping criterion is fulfilled. The Python package *DEAP: Distributed Evolutionary Algorithms in Python* is used for the practical implementation in this work (Fortin et al., 2012) (de Rainville et al., 2012).

2.3.3 Parameter tuning

The design and implementation of GA offers a large degree of freedom. Thereby, it holds the potential for an optimization of the applied settings. In fact, a proper parameter tuning can make the difference, in how close a solution gets to the true Pareto front, and in how quick a convergence towards the Pareto front is achieved (Simon, 2013). For the GA applied in this work the following parameters were identified to be most significant:

1. Initial population factor f_{MX}
2. Regular population size n_{pop}

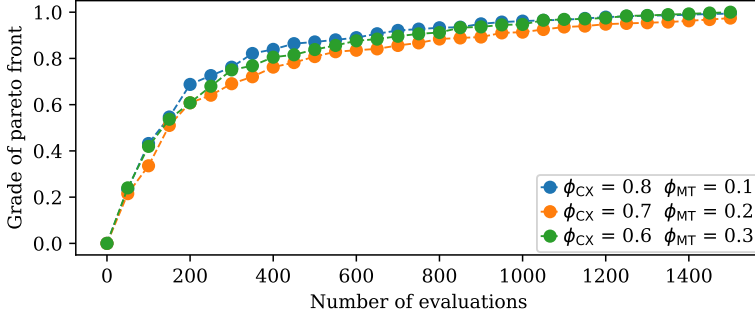


Figure 2.19: Evolution of population grade for the best three settings formed by the cross probability ϕ_{CX} and the mating probability ϕ_{MT} .

3. Crossover probability ϕ_{CX}
4. Mutation probability ϕ_{MT}
5. Number of generations n_{gen}

These tuning parameters can be divided into two groups. The first group does not affect the total number of EA function evaluations and consists of f_{MX} , ϕ_{CX} and ϕ_{MT} . As a matter of fact, among these factors the initial population factor f_{MX} needs some further argumentation on because it actually increases the number of necessary simulation runs per optimization case. Nevertheless, since the initialization is not a core part of the GA and can be done using various different approaches (e.g. randomly, using expert knowledge or linear programming) it is further assumed to belong to the first group. In contrast to that, the tuning parameters n_{pop} and n_{gen} of the second group have the potential to directly affect the number of EA function evaluations. However, this is only true if either one of them is changed while the other one is constant. Therefore, to achieve a fair comparison among different parameter sets the total number of EA function evaluations according to the following equation is assumed to be constant.

$$n_{eval} = n_{pop} \cdot n_{gen} \quad (2.23)$$

To assess the influence of the aforementioned tuning parameters, variation runs of the GA are conducted. In each run $n_{eval} = 1500$ EA function evaluations are done. This ensures good convergence for all tested parameter settings.

Figure 2.19 comprises the three best settings, that were tested. It shows the average grade of the Pareto front after conducting 50 full EA repetitions. Although their overall performance after 1'500 evaluations is comparable, the setup using a lower mutation rate of 0.1 shows better performance at the beginning. Additionally, the lower mutation rate reduces the average diversity of the EA. This leads to roughly half the computational effort compared to the other settings since already evaluated individuals are not simulated again. For these reasons, $\phi_{CX} = 0.8$ and $\phi_{MT} = 0.1$ are chosen as final GA probability parameters.

Having defined the aforementioned GA parameters leaves only the stopping criterion as an open question. Several options exist for the termination of a GA, from which the following three methods are the most popular (Michalewicz, 1996):

- Maximum number of generations
- Maximum number of fitness functions evaluations
- Low chance of achieving significant changes

The optimization problem considered in this thesis comes with a very expensive fitness function. Therefore, a predefined end of the algorithm is preferable, which reduces the uncertainty on the GA run time. This way, time intensive computations that only reveal minor improvements of the Pareto front can be prevented. The first two methods both ensure this desired behavior. However, some further knowledge about the optimization problem with respect to its convergence is needed to allow the estimation of a reasonable search length.

With respect to that, the convergence behavior of the considered algorithm is analyzed using a statistical approach. Figure 2.20 indicates that late evaluations of the algorithm hardly improve the grade of the Pareto front, which leads to unreasonable computational effort. To prevent this, a relaxed convergence criterion is considered in the further study, which defines sufficient convergence to be 99 % of the final grade after 1'500 evaluations. Further, we assume a 95 % confidence interval, that needs to be fulfilled by the GA parameter test data. Following this approach the necessary number of evaluations per optimization run can be found slightly below 1.000. With this analysis the value of evaluations is chosen to be 1'000 for any further optimizations.

2.4 Optimization scenarios

The following section introduces the optimization scenarios that are considered in this work. In a first part the thermal demand structure and its relevance for the design optimization is presented. Afterwards, the properties of the DS with the corresponding grid load situations are explained. Finally, the last part deals with the structure of the NES, where the reference scenario and applicable projections are elaborated. Each section gives an overview

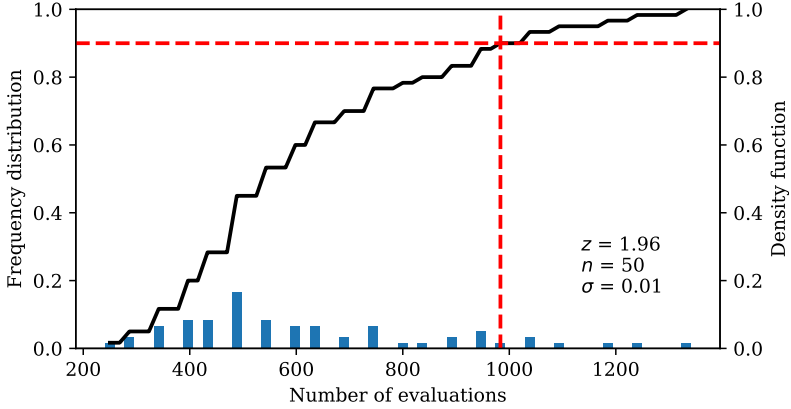


Figure 2.20: Histogram of minimum number of evaluation for GA convergence.

on the domain-specific variations that are considered. Every combination of these variations is investigated using a mixed or marginal assessment method. This leads to a total of 216 different scenarios that are optimized in this work. A reduced set is analyzed in detail in chapter 4. General conclusions are made on how different contexts effect the optimal design of grid-driven CG systems.

2.4.1 Thermal demand structure

Depending on the operation mode (heat-driven vs. electricity-driven), the main operational restriction of CG system is the thermal or the electrical demand. However, the systems considered in this thesis pursue two potentially conflicting goals. First, the thermal demand of a residential building must be met. Second, a service to the energy system is should be delivered in a most beneficial way.

However, in the CG concept at hand, the thermal demand supply is a necessary condition to fulfill, which in turn makes the thermal demand the main operational restriction. In that context the sorted heat duration curve (HDC) is an important measure for a suitable system dimensioning. The sorted HDC comprises the thermal load situation of a building for a specific period in descending order. Information on how long a building exceeds a particular thermal load can be gathered this way, which gives a good indication on the annual operation of a CG system depending on its thermal heating capacity. In the field of residential buildings a HDC usually comprises the thermal demand for SH and/or DHW.

The suitability of a CG unit to supply a building with heat depends on several factors. Generally, CG systems perform better the more full load operation hours (FLH) can be achieved. These FLH strongly depend on the shape of the sorted heat duration curve of a building. Due to its convenience, the HDC forms the basis of commonly used sizing approaches, such as "5.000 full load hours" or maximum rectangle approach (Haeseldonckx et al., 2007)(Gelegenis and Mavrotas, 2017).

In contrast to most existing sizing approaches, the presented design approach does not explicitly rely on the HDC concept. Instead, it uses the sorted HDC as an indication for the thermal demand structure of a building. In that sense, thermal demand curves can be classified according to their structure and a distinctive set can be picked for the further analysis. For this purpose quantitative values of the heat load itself are unimportant, which means that dimensionless curves can be used. This way, more general conclusions on the optimal design of grid-driven CG systems can be drawn.

Like the traditional approaches, the new design approach is affected by the shape of the HDC. With respect to that, three main drivers can be identified:

- Retrofit state or insulation standard of the building envelope
- DHW demand profile
- Internal heat gains caused by occupants and appliances

To further elaborate on the aforementioned factors, figure 2.21 shows relative sort HDCs of a 1000 m² MFH built in 1985. The variations shown in the figure correspond to different retrofit levels and occupant densities A_{occ} which defines the available floor area per occupant.

The influence of the retrofit level can be clearly recognized by higher heat demand during the entire heating period for the original retrofit state. In addition to that, the thermal peak load for a non-retrofit building is significantly higher which leads to a steeper trend. At around 6.000 hours the HDC of the original building shows a down-step that indicates the transition to the summer period. This step is not found for a retrofit building due to a comparably shorter heating season. Following these observations confirms that the retrofit level significantly affects the peak load in the left and the intermediate load in the middle section of the HDC.

The thermal demand introduced by DHW preparation occurs during the whole year. Nevertheless, DHW demand is capable of producing high thermal peak loads depending on the installed preparation system. In the presented methodology a TES integrated DHW station is assumed. The buffering effect of the TES leads to rather smooth thermal demand curves for DHW preparation in that case which shows a base load character. Usually, only a minor seasonality occurs due slightly lower fresh water temperatures during winter. The seasonal character of SH and DHW demand differs largely and with respect to that a significant influence on the operational restrictions of a CG system must be assumed. In the following,

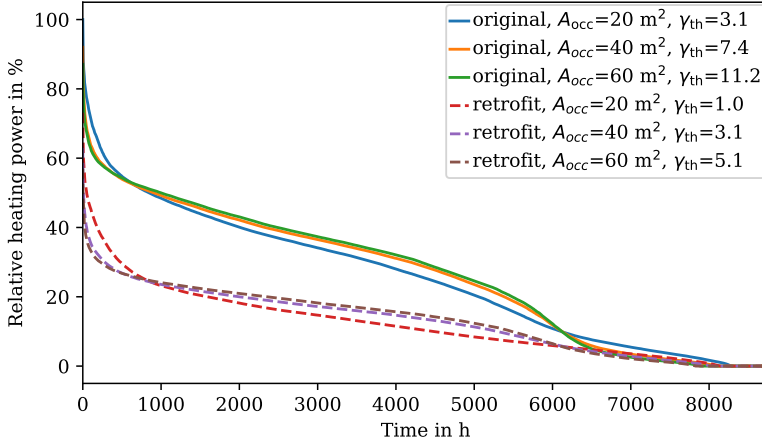


Figure 2.21: Heat duration curves of an exemplary MFH with different retrofit levels and occupant floor areas A_{occ} .

this effect is incorporated using a thermal demand ratio $\gamma_{th} = \frac{Q_{SH}}{Q_{DHW}}$. The third important influencing factor for the HDC shape are the internal thermal gains within a BES. Just like the DHW demand internal gains occur during the entire year. In contrast to DHW, internal gains are able to reduce the overall thermal demand of a BES. A potential demand reduction however only affects the SH demand, which temporally limits their effect on the heating season.

Looking closer at the three factors above reveals that the DHW demand and the internal gains are determined by the number of occupants and their behavior with respect to DHW, activity level and usage of electric appliances. To represent both aspects while remaining comparability between differently sized buildings the occupant density A_{occ} is defined. The combination of different retrofit levels and occupant densities allows for describing distinct relative thermal demand structures.

Regarding the CG's potential to achieve low CO_2 abatement cost the absolute size of a device is important. Larger units offer higher electrical efficiencies at lower specific investments. Therefore, buildings with a higher absolute thermal demand are expected to feature a cheaper CO_2 abatement. In that sense, two different MFHs with 500 and 1000 m^2 floor area are considered in the optimization scenarios. With respect to the grid interaction buildings with a floor area above 1000 m^2 are often connected to the medium voltage level and would not affect the local DS. For that reason, larger buildings are not in the scope of this analysis.

2.4.2 Distribution system context

One of optimization objectives is the mitigation of grid congestions in a local DS. But of course, a mitigation implies a certain demand for congestion management. In this respect, DS scenarios that are characterized by different congestion power demand levels are presented in the following. Grid congestions can arise from high loads or injections that are expected to increase in the near future. Main drivers are the introduction of HP and EV on the load side and PV for the injection. To address these aspects different penetration levels with the aforementioned technologies are considered in the DS context and are presented in the course of this section.

In addition to the technology penetration the network topology has a significant influence on the operational resilience of a particular DS. Therefore, a suitable DS case for the analysis needs to be assumed. To be able to draw more general conclusions benchmark DS were considered instead of real life examples (Dickert et al., 2013). From the set of available benchmark grids a low voltage grid representing a suburban topology is chosen. A suburban grid is very likely to incorporate all of the aforementioned technologies while at the same time providing a mix of residential SFH and MFH. This way the need for congestion management as well as the potential mitigation by CG units can be assessed in a realistic environment.

The technology penetration level within a district and the corresponding DS is very much determined by several factors. First, the retrofit level of the buildings within a district is important since it determines suitable heating technologies. For retrofit or new districts a higher share of HP as primary heating systems can be expected. Further, the available average income influences if new technologies like HP, EV or PV are adopted and are actually deployed within a district. In this study a transformation towards retrofit buildings and advancing electrification of heating and transport is expected. This process is further accompanied by the deployment roof top PV systems.

For the considered scenarios the above technologies are combined to a general electrification level within a district. With respect to that, three electrification levels (33%, 50% and 67%) are assumed that directly take effect on the congestion power demand. Herein, a 33% electrification level means that 33% of the households within a district are equipped with a

- roof top PV panel
- electric HP (only SFH)
- one EV for two persons

The reference heating system for MFHs is a condensing GB since these are equipped with CG units in the optimization cases. Technical details on the DS context implementation can be found in chapter 3.

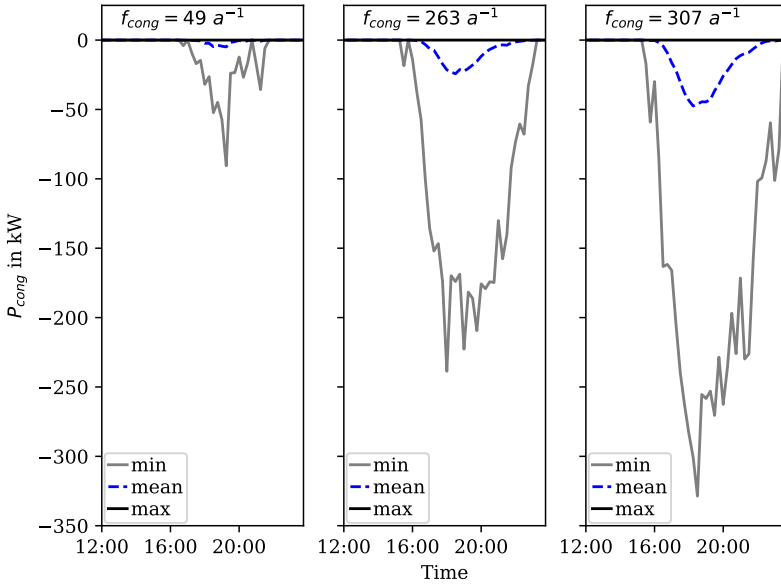


Figure 2.22: Classification of different congestion power scenarios using statistical measures for a low (left), medium (middle) and high (right) level of electrification.

Applying the different electrification levels with the corresponding electric load and generation profiles in a PFC results in three annual congestion power curves for the suburban DS. These congestion power curves describe the DS context for the optimization procedure. To enable better comparability between the individual cases the congestion power demand is statistically processed. The result is depicted in figure 2.22 with an increasing electrification level from 33 % on the left to 67 % on the right. For each electrification level only days with a grid congestion were included resulting in the annual congestion frequency f_{cong} . Based on this reduced set of daily congestion power curves the minimum, maximum and mean value for each time of the day were calculated.

Comparing the different cases reveals large differences in the demand for congestion management. The first scenario which corresponds to an electrification level of 33% shows only 49 congested days per year whereas the 67% scenario necessitates congestion management for 307 days per year. Also the mean demand for congestion power is significantly higher in the 50 and 67% scenarios. Together with the high frequency of occurrence in both latter cases a congestion situation should be rather considered as the norm not an exception.

The minimum values shown in the figure are extreme values for each hours that only occur once in a year. Nevertheless, many hours even in a congested day do not require any action which is indicated by the zero minimum line and the limited time window. It can be noted that especially around 19:00 am a significant risk for a grid overload exists. These peaks are mainly caused by EV due the high probability of charging events when people return from work. Additional congestions that occur later in the evening mostly originate from a combination late EV charging and electric HP systems that go into operation when ambient temperatures drop.

2.4.3 National energy system context

The NES representation used in this study is mainly defined by the national power generation portfolio and the structure of electric loads. The year 2017 is defined as reference case. Starting from there two different projections for the year 2030 are analyzed. In the following the energy transition's main drivers that are taken into account with this work will be presented. These are expected to be:

- Phase out today's base load power plants (i.e. coal and nuclear)
- Increased share of RES in power generation
- Electrification of heating and transport
- Increased prices for CO₂ emission allowances

An overview on the installed conventional and renewable generation technologies that are accompanied by electrical storage capacities is given in figure 2.23. These capacity projections correspond to the German grid development plan and cover a reference scenario based on the year 2017 numbers as well as two scenarios for the year 2030 (Bundesnetzagentur, 2018b). In addition, the exact figures in the considered scenarios are listed in table A.3.

Within the next two decades today's base load power plants are foreseen to phase out completely. The final shutdown of all nuclear power plants is already scheduled for 2023, whereas the decommissioning of coal-fired power plants is likely to be in 2038. Already for the year 2030 the share of coal-based power production will be significantly reduced. The lost dispatchable generation capacities will be partially replaced by gas-fired power plants. Nevertheless, the total installed conventional capacity will be reduced.

Besides the phase-out of nuclear and coal the deployment of renewable power generation assets persist. Especially PV and onshore wind power are expected to cover significant shares of the national electricity demand. To reach this target, large renewable generation capacities need to be installed according to 2030 scenarios. These RES will be accompanied by a slight increase in pumped hydro capacity. However, a more important role for the integration of renewable

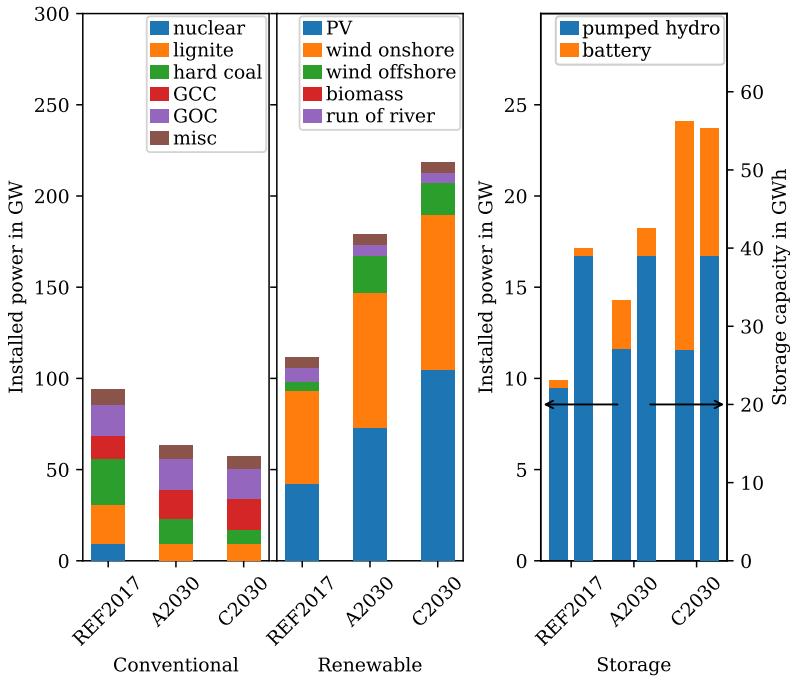


Figure 2.23: Power generation and storage portfolio for different NES scenarios of 2017 and 2030 (Bundesnetzagentur, 2018b).

power is connected to battery storage systems. Although, in 2017 this technology only had a negligible installed power and capacity its contribution will grow with larger capacities in different applications.

Comparing the 2030 projections shows that the A2030 case is characterized by a moderate transformation towards RES and a slower phase-out of coal-fired power plants. In contrast to that, the more ambitious scenario C2030 relies strongly on power generation from PV, whereas especially hard-coal capacities are reduced even more.

Whereas the non-residential electric load is out of scope and is therefore left unchanged compared to the reference year 2017, the residential load is influenced by the considered technology adoption. Regarding the national residential load the electrification of heating and transport are taken into account. Both applications are expected to expand their share in the national electricity demand. In that sense, the penetration with EV and the individual heating tech-

nology shares, e.g. electric heat pump, are an important factor. Tables A.1 and A.2 of the appendix list the assumptions that form the basis for the calculation of the residential electric load, including EV charging and heating applications.

In accordance with the less ambitious renewable power generation share in scenario A2030, a moderate level of heating electrification is assumed. Instead, A2030 shows a technology mix in which fuel-based and electric heating systems coexist. In contrast to that, scenario C2030 follows a consistent transformation towards renewable power generation and electric energy demand.

Looking at the above mentioned technological trends, especially the phase-out of base load power plants could have a strong impact on the emission intensity and the wholesale price of electricity. For the nuclear phase out a base load capacity replacement by carbonic fossil fuels is very likely, at least for a significant amount of produced electricity. As a consequence, the average CO₂ intensity is likely to increase in comparison to power from nuclear plants.

The coal phase-out is differently related since it will be compensated by large renewable capacities and gas-fired power plants. Generally, these show a lower CO₂ intensity in comparison to coal-fired power plants which holds the potential to reduce CO₂ emissions stemming from power generation. However, when considering the marginal power generation cost in a future market the price for CO₂ emission allowance is able turn over the existing merit-order. It creates a stronger correlation of emissions and generation costs.

The effect can be seen in figure 2.24 for the REF2017 and C2030 scenario. Whereas the REF2017 merit order shows only little changes with the inclusion of CO₂ emission allowance cost, a major upward shift of the curve and change in positions for hard coal and GCC can be identified in C2030. Such positional changes in the merit order have a large impact for the marginal CO₂ intensity since they swap the marginal power plant type in a particular load bandwidth.

The price for CO₂ emission allowances is likely to increase until 2030 where a range from 30 to 100 €/tCO₂ is expected. Within the presented scenarios A2030 and C2030 a price of 30 €/tCO₂, respectively 50 €/tCO₂ is assumed. Considering the aforementioned effects the CO₂ intensity and power prices are calculated according to the presented methodology (cf. 2.1.1) using the corresponding generation portfolio, electric loads structure and CO₂ emission allowance prices. The resulting price and CO₂ intensity curves are statistically processed and presented in figure 2.25

The left part of the figure shows the 25 % and 5% percentiles as well as the mean values of the emission intensity and power price. It can be seen that the average CO₂ intensity clearly decreases until 2030 both scenarios with a slight advantage for the C2030 case. This advantage originates in the lower share of coal-fired power plants compared to A2030. Regarding the fluctuation bandwidth only a minor increase due to higher shares of RES can be recognized. In

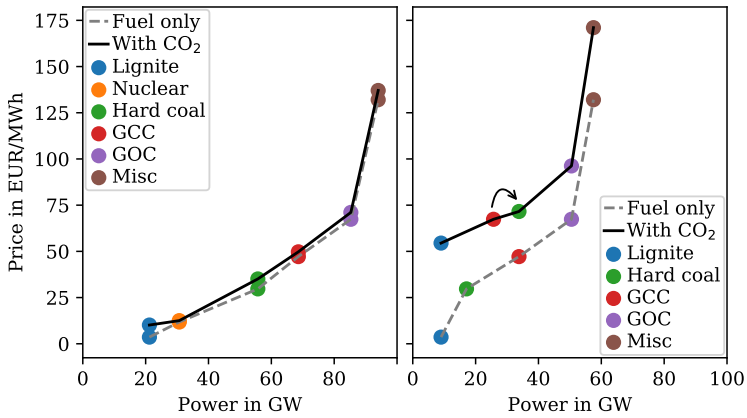


Figure 2.24: Merit order of conventional power plants for the scenarios REF2017 (left) and C2030 (right). The gap between the curves indicates an increasing price effect of CO₂ allowance certificates for future scenarios.

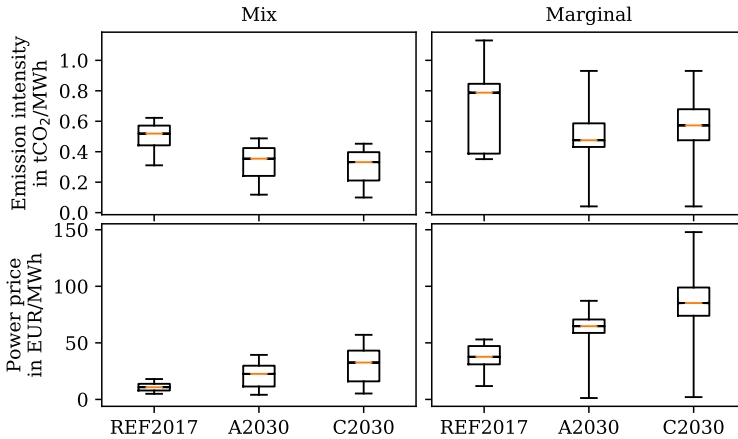


Figure 2.25: Statistical comparison of the annual emission intensity and power prices for different scenarios of 2017 and 2030.

contrast to the emission intensity the average generation cost as well as the level of fluctuations increases noticeably. The upshift is mainly caused by the growing prices for CO₂ emission allowances whereas the higher fluctuation stems from the significant share of renewable power generators.

For the marginal signals on the right side a different picture is drawn. Although a decrease of the average emission intensity can be seen for both 2030 cases the C2030 scenario performs slightly worse. The aforementioned positional swap in the merit order often causes hard-coal power plants to be the marginal technology. Additionally, a higher PV share and its reliable day and night fluctuation fosters the operation of power plants that are on the high side of the merit order. This effect emerges even stronger within the power price curves and leads to significantly growing average values and high fluctuations within the 2030 scenarios.

3 Modeling and Simulation

After having presented the methodology which is applied in the course of this work, the models used in the analysis will be explained in detail. An overview on how the different links of the tool-chain work together is shown in figure 3.1.

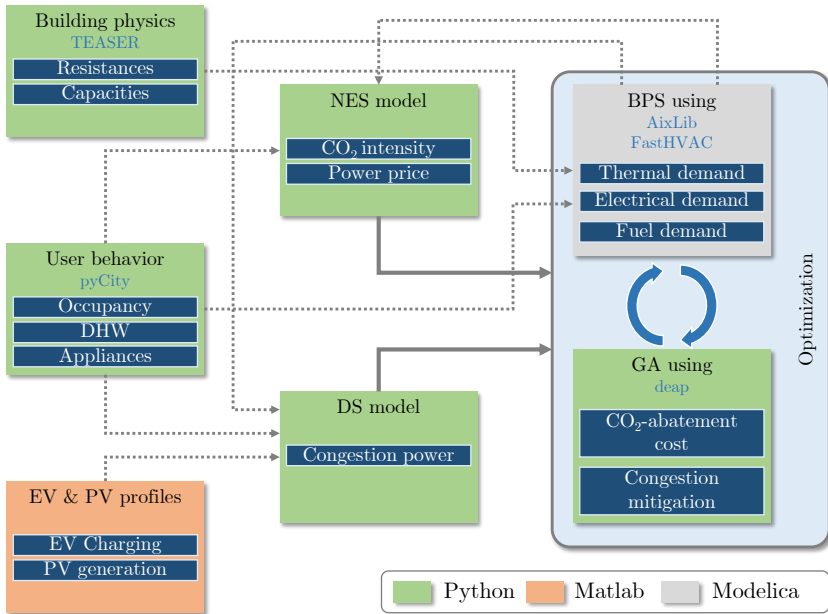


Figure 3.1: Schematic of utilized tools for parameterization and input data.

Each tool-chain component has a specific color indicating the programming language. The most important output values of each element can be found in the blue boxes. Further, the connections can be distinguished into dashed lines for pre-processing and solid lines which indicate the final optimization inputs. Besides the Python and Matlab tools on the left, building performance simulation (BPS) is applied for a first time during this pre-processing phase to derive suitable thermal and electrical building demand profiles. In a subsequent step these demand profiles are fed into the NES and DS model. The iterative optimization

procedure itself is then executed using the time-resolved CO₂ intensity and power price curves from the NES model and the congestion power demand from the DS model.

3.1 BES model

The considered energy system is subject to a high complexity, which is why the analysis within this work relies on dynamic simulation models. The application of BPS with physical models enables a detailed representation of the BES with all its components and provides helpful insights into system behavior in a dynamic grid context. An overview of the BES is given in figure 3.2.

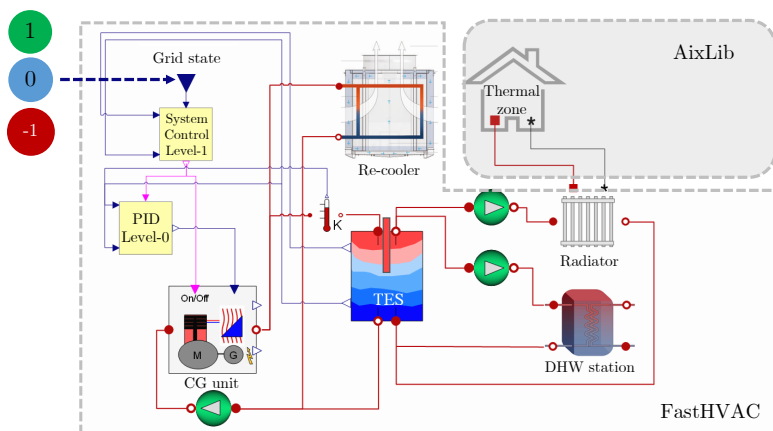


Figure 3.2: Schematic of BES model in Modelica. The system is modeled using the library AixLib. The supply side model is based on the subpackage FastHVAC.

In the considered BES a thermal building model is connected to a heat emission system. A CG unit generates heat that is fed into a TES. Besides storage capacity, this TES provides a time-wise decoupled link between thermal supply and demand. The models of the individual components that form the BES will be explained in the following.

3.1.1 Building model

The purpose of the building model is to simulate the behavior of a thermal zone under given environmental conditions. It is a representation of the building envelope and the thermal

inertia of a building. In this thesis the building model is used within a GA which necessitates a large number of iterative simulation runs. With respect to that, a low computational effort is a prerequisite to the used models. Additionally, a reasonable accuracy is needed to acquire reliable simulation results.

With respect to that, a reduced order model as suggested by Lauster et al. (2014) is a suitable trade-off for the considered application. Herein, the thermal behavior of the building is implemented as an equivalent thermal network comprising resistances (R) and capacitances (C). Physical properties of a building, such as geometry and wall construction, can be converted to corresponding R and C values (Verein Deutscher Ingenieure e.V., 2012).

However, in this work no particular building but rather a building category, i.e. MFH, is subject for an analysis. Therefore, the archetype buildings developed within the EU research project TABULA are considered (Loga et al., 2016). For a convenient generation of the corresponding parameters the open source tool *TEASER* is used (Remmen et al., 2017). The aforementioned reduced order building model is part of the open source Modelica library *AixLib* (Müller et al., 2016).

3.1.2 HVAC models

Apart from a thermal zone model the BES also comprises HVAC equipment, such as CG and TES. The requirements regarding computational efficiency must hold true for these models as well. With respect to this, again a reduced order modeling approach was chosen that implements only necessary thermal effects within the system components and the hydronic circuit. In comparison to ordinary 1D fluid models, pressure calculations are omitted and instead only mass flow rates and enthalpy flows are considered. A validation of this reduced order approach revealed only negligible deviations while reducing the computational effort significantly (Stinner et al., 2015). Besides, the disregarded energy demand of the BES's circulation pumps only accounts for a minor share of the overall energy demand of a building. The aforementioned modeling approach is applied in the Modelica library *FastHVAC* that provides models for an internal combustion engine based CG device and a multi-layer TES among other models.

Since the effective storage capacity of a TES strictly depends on the temperature in different storage layers a 1D stratification model is implemented. Thereby, enthalpy flows between the storage layers can be determined. Besides, the conductive heat transfer from one layer to its neighboring layers and to the ambient air is considered. Possible stratification inversions resulting from high return temperatures of the heat distribution system are considered with a buoyancy model. Herein, the buoyancy effect is implemented as an artificial diffusion term that superposes with the ordinary diffusion. A model validation revealed good accordance with measurement data for charging and discharging (Linden, 2015). To cover peak heat

demands that the heat emission system draws from the TES an electric HR can be utilized. This peak load HR is installed in the top of the TES and is meant to ensure a minimum allowable flow temperature in the top storage layer.

The CG model used in this work is equation-based following Gelegenis and Mavrotas (2017). With the desired relative output fed into the model by the level-0 PID controller the CG model calculates the corresponding thermal and electrical power that can be delivered. Further, the fuel mass flow rate to fulfill this working point is determined. The design of a grid-driven CG system in a dynamic grid context depends on both the sizing and the operation of the system Pruitt et al. (2013). In this regard, the thermal startup and stopping characteristics of the CG device are implemented using a first-order delay with a specific time constant. Further, the part-load efficiency is considered following equation (3.1). In addition, control characteristics that affect the time variant behavior, such as ramping capability, minimum operation time per cycle and blocking time after shutdown are of importance. These effects are incorporated within the level-0 device controller.

$$\eta_{el}(P_{el,rel}) = \eta_{el,rat} \cdot (0.261 + 0.161 \ln(P_{el,rel})) \quad (3.1)$$

To include the demand side of the BES as well, heat distribution system models for SH and DHW are implemented. Both are based on multi-layer HEX that consist of connected discrete fluid volumes (cf. TES model). A radiator model including a thermostatic valve is connected to the thermal zone model. It delivers the necessary thermal energy to keep the thermal zone temperature at the desired set-point of $T_{set,room} = 20^\circ\text{C}$. The radiative and conductive heat flow is determined by the temperature difference between radiator and the thermal zone. The second heat distribution model is a DHW station that comprises a discretized plate HEX. It models the counter-flow heat transfer from the heating fluid to the freshwater.

Return flows of the both HEX types vary in temperature over the year depending on the thermal energy demand of the building and its inhabitants. With a high SH demand in winter a warmer return flow from the radiators can be observed. The back-feed of the heating fluid into the lower layers of the TES leads to a reduced effective temperature spread which results in a smaller usable storage capacity. To take this effect into account is therefore an important factor with respect to the operational flexibility of a CG system.

In contrast to ordinary CG systems an RC option is considered in this analysis as well. The re-cooling device is able to dump excess thermal energy in case the operation of the CG system is beneficial due to grid requirements. For that purpose, an air-cooled flatbed drycooler is used which conditions the return temperature of the CG unit (cf. figure 3.2). A reduced order model of the re-cooling device is implemented in this work using a table-based approach. Depending on the desired cooling power the electric power demand of the re-cooler

fans is calculated according manufacturer data (Güntner GmbH & Co. KG, 2019). The power demand is covered by the CG system onsite and reduces the system's electricity feed to the grid.

3.2 Power system models

When analyzing grid-driven distributed CG in a dynamic grid-context the representation of the surrounding power system constitutes an essential part of the methodology. To cover all necessary effects in the power system a well-balanced modeling approach needs to be applied. Even more than in the BES domain negligible relations need to be identified and consequently omitted within a model. The following sections present the models that were used to simulate the NES and local DS which together form the hybrid dynamic grid context within this study. While the NES model assumes no grid restrictions from a physical point of view (i.e. copper plate), the DS model explicitly considers this aspect in detail.

3.2.1 National energy system model

The power system state is an essential element in the proposed methodology. As shown in the tool chain overview the result of the power system model forms the grid inputs to the BES models and thereby it transmits the power system state information to the BES controls. The models that are used to obtain the aforementioned information are presented in the following. Figure 3.3 provides an overview on the main parts of the NES model.

The NES model considers the German power market. In that respect, structural information on the German power market is needed. Especially the installed capacities of committable conventional power plants and renewable power generators are of great importance. Further, the electric loads that are connected to residential buildings or districts need to be integrated into the modeling approach. EV charging loads and electric loads stemming from heating applications are found to be crucial here since they are expected to increase in the next decades. To properly model the aforementioned electric power generators and loads, the installed capacities of each technology need to be identified. In accordance with the identified structure, the three main sub-models of the power system are developed. Combined, these models are used to calculate a full year power plant dispatch. In the following the individual models will be presented.

Three different electric load categories are considered in the model:

- Electric loads from heating applications
- EV charging loads
- Residual loads from other applications (e.g. industry and commercial)

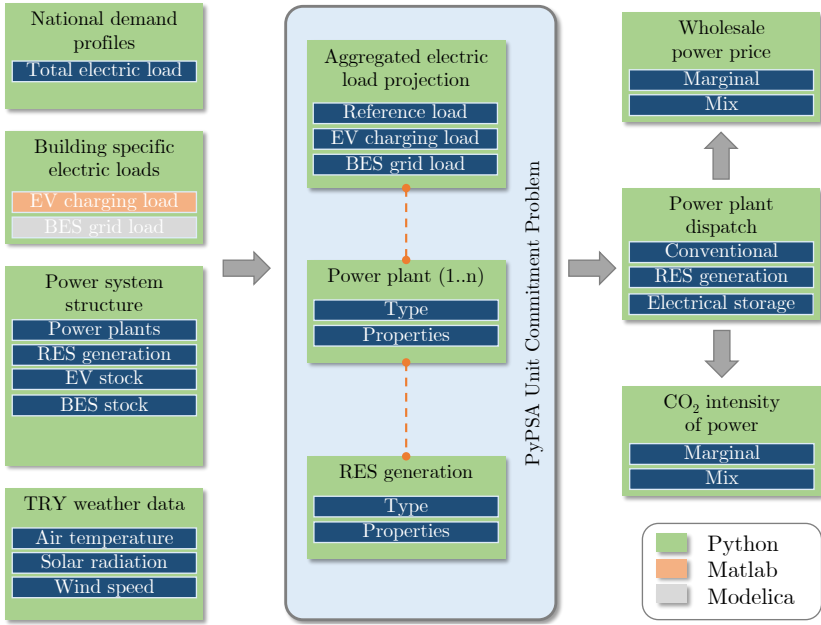


Figure 3.3: Components of the power market model with an indication of the utilized programming languages. Input data streams depicted on the left. The central element is the unit commitment problem implemented with PyPSA.

Whereas the first two are explicitly modeled in the presented approach, the residual loads are out of the scope of this study and are therefore assumed to be unchanged. However, they are identified by subtracting the modeled loads for heating and EV charging from the national electricity load of the reference year 2017. The electrical load for heating applications depends on the utilized heating technologies and thermal demand structure which is mainly defined by

- Building types
- Retrofit states
- Geographical locations

In a first step, based on this classification thermals loads for every possible combination are calculated using a reduced order building model as presented in 3.1.1. Results from a BPS of each combination obtain a set of thermal loads grouped by building type, retrofit state and geographical location. Next, these thermal load profiles are scaled according to their absolute

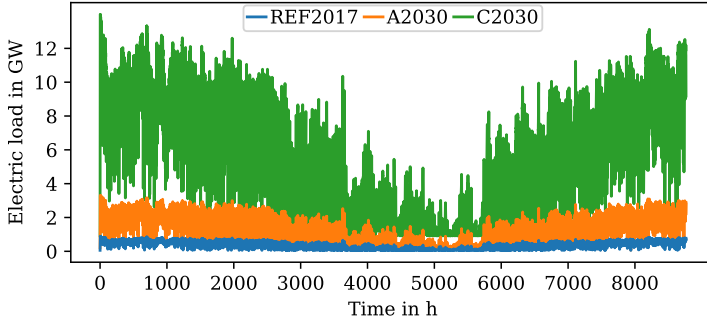


Figure 3.4: Electric loads of different scenarios for 2017 and 2030 originating from HVAC systems, i.e. SH and DHW.

national heat demand and afterwards composed following their percentage of occurrence. The scaled composition represents the national thermal demand profile. Although different retrofit states and locations were combined a distinction between SFH and MFH still remains.

For the NES model not the thermal demand profiles but the electric grid interaction of a building is of interest. This grid interaction depends on the buildings' HVAC technology and the corresponding power-to-heat-ratio. According to the HVAC technology share for a particular building type, thermal demand profiles are converted to electrical demand profiles. The result of the presented approach is given in figure 3.4. It shows the national electric load related to the supply of SH and DHW demand.

The structure of the demand curves shows a clear seasonality with high demands in winter and lower demands in summer. Furthermore, a daily fluctuation can be identified which is mostly due to day-to-night changes of the ambient temperature. Besides the DHW demand during the night is low. In addition to that, the scenarios presented show significant differences that are mainly induced by the dominant HVAC technologies. Whereas REF2017 has only little shares of grid connected heating systems, C2030 comprises a large number of electric heat pumps. In scenario A2030 a technology mix is assumed in which heat pumps and CG systems co-exist. In turn, the balanced electric load stemming from heating applications is reduced.

Regarding the electrical loads profiles from EV charging a Matlab tool is used (Schlösser, 2019). The tool calculates an annual charging profile of a single EV based on a stochastic method. It exploits the strong correlation of EV charging events with the recurrence of a building occupant. In that sense, the returning phase of an occupant can be modeled using a probability distribution over time. For each day the start time of a charging event is drawn from the distribution. Beyond the times of daily charging events the daily electricity demand

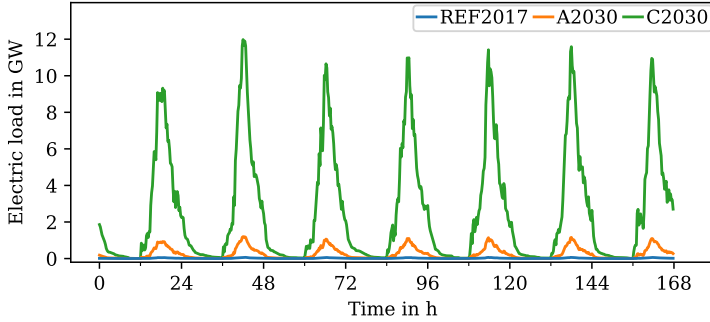


Figure 3.5: Exemplary electric loads in first week of April stemming from EV charging in different scenarios of 2017 and 2030.

of the EV and the installed EV charger power needs to be taken into account. To cover the aforementioned aspects, technical properties of five different EV usage types and four charger types are considered in the model (Uhrig, 2017). For each possible combination 120 profiles are calculated. Based on that, a shuffled choice from the available combination profiles is used to create a national EV charging profile that corresponds to EV usage shares, installed charger capacities and the total number of EV. An exemplary EV charging profile for the first week of April is presented in figure 3.5.

The EV demand curves reveal that in the REF2017 scenario the share of EV is only at a negligible level. Nevertheless, EV charging loads need to be taken into account as the 2030 demand curves show. Especially C2030 which constitutes the heavy electrification scenario shows high demand peaks during the evening hours that partially coincide with high demands from heating applications. Comparing electric loads from heating applications and electric mobility, both demand types show high peak demands that are in the same order of magnitude. This fact emphasizes their significance for the NES and justifies the effort to model them.

A further important component within the NES model is the renewable power generation model. It represents the non-dispatchable generation assets in the NES, such as (on- and offshore) wind power and PV systems. The actual output of both technologies depends on the weather conditions on the one hand and on the grid hosting capability on the other hand. Wind power and PV models both rely on weather data of different locations in Germany (cf. 3.3.1). Besides, structural information on the installed capacities and electricity production data in the reference year 2017 are used to tune and validate both models (Bundesnetzagentur, 2019). In the following, the renewable generation model applied in this study will be explained along the example of wind power.

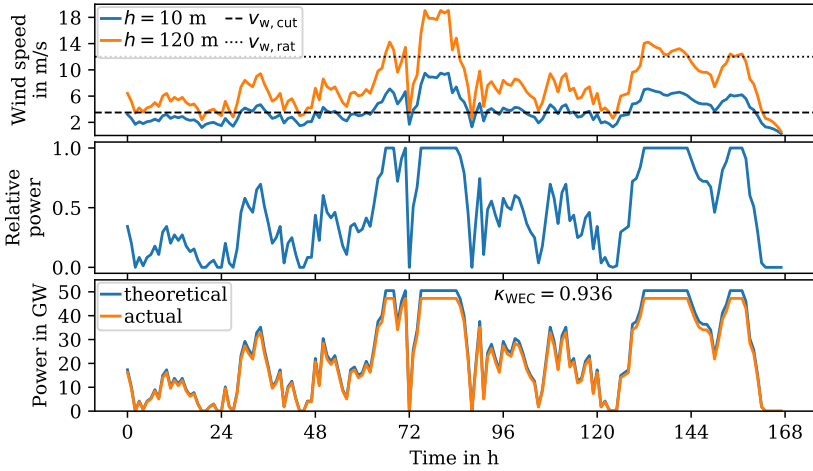


Figure 3.6: Calculation of wind power generation for exemplary week in October (C2030) based on wind speed and relative power.

In general, the wind power generation at a specific location depends on the available wind speed. Since the wind speed shows significant differences among locations across Germany multiple sub-locations need to be analyzed and combined afterwards. For this purpose, the four grid balancing zones of the German power market are considered. Each of these zones is modeled using a representative sub-location. However, the TenneT balancing zone which diagonally spreads through the country is an exception (TenneT, 2020). Here, a subdivision into a wind dominated northern zone and a PV dominated southern zone with their corresponding representative locations needs to be conducted. Furthermore, generation from offshore wind parks needs to be represented by an offshore location.

Based on weather data of a particular sub-location the wind power generation curve can be calculated. The necessary steps will be explained in the following along the equations 3.2 to 3.5. Figure 3.6 shows the results for each step for an exemplary week in October in the grid balancing zone of Amprion.

In a first step, a height correction of the wind speed data that is measured in a height of 10 m needs to be performed. For that purpose equation 3.2 can be used (Quaschnig, 2019).

$$v_a(t, h) = v_{a,10}(t) \cdot \left(\frac{h}{10 \text{ m}}\right)^z \quad (3.2)$$

Since the weather data corresponds to locations nearby cities or townships a roughness factor of $g = 0.28$ is applied (Kleemann and Meli, 1993). The average generator height of wind energy converters (WEC) that are in operation in the year 2030 is assumed to be 120 m (Keiler and Huser, 2017). Usually, WEC need a cut-in wind speed for startup $v_{a,\text{cut}}$ and reach their maximum output at the rated wind speed $v_{a,\text{rat}}$ (Quaschnig, 2019). Both values are indicated in the upper part of figure 3.6.

Using these values the relative wind power is defined by equation 3.3. It represents the power output of an entire sub-location in relation to its installed wind power capacity. In theory, the output of a WEC depends on the wind speed with a power of three. However, practical applications show a rather linear connection of wind speed and power output in the range between $v_{a,\text{cut}}$ and $v_{a,\text{rat}}$.

$$\nu_{\text{WEC}}(t) = \begin{cases} 0 & , \text{ if } v_a(t) < v_{a,\text{cut}} \\ \frac{v_a(t) - v_{\text{cut}}}{v_{\text{rat}} - v_{\text{cut}}} & , \text{ if } v_{a,\text{cut}} \leq v_a(t) \leq v_{a,\text{rat}} \\ 1 & , \text{ if } v_a(t) > v_{a,\text{rat}} \end{cases} \quad (3.3)$$

The relative wind power curve $\nu_{\text{WEC}}(t)$ corresponds to the power generation curve per installed capacity. Based on it, the theoretical wind power curve can be found by multiplying with the installed WEC capacity $\hat{P}_{\text{el,WEC}}$, as presented in the lower part of figure 3.6. However, a capacity reduction factor according to equation 3.4 needs to be taken into account.

$$\kappa_{\text{WEC}} = \int_0^{t_{\text{year}}} \nu_{\text{WEC}}(t) dt \cdot \frac{\hat{P}_{\text{el,WEC}}^{(2017)}}{W_{\text{el,WEC}}^{(2017)}} \quad (3.4)$$

This factor ensures that the calculated wind energy using TRY weather data equals the actual generation $W_{\text{el,WEC}}^{(2017)}$ of the reference year 2017. On the one hand, the difference between measured and simulated data can be explained by inevitable model errors. On the other hand, this κ_{WEC} also considers that the availability of a WEC is usually below 100%. With the above equations the actual wind power generation for a specific location is determined by equation 3.5.

$$P_{\text{el,WEC}}(t) = \nu_{\text{WEC}}(t) \cdot \kappa_{\text{WEC}} \cdot \hat{P}_{\text{el,WEC}} \quad (3.5)$$

The presented modeling approach for wind power generation is applied for PV systems in a similar way. Instead of wind speed, the total solar irradiation in a representative location is considered as main environmental factor. In contrast to WEC, no correction to the weather

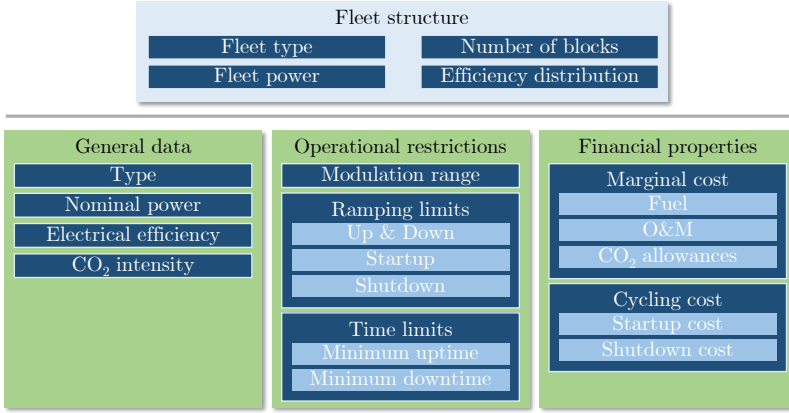


Figure 3.7: Schematic of the applied power plant model.

data is done. Further, no cut-in or rating threshold is applied which leads to the assumption of a linear correlation of solar irradiation and actual power output.

Conventional power generation by fossil-fired power plants is a further essential part in the NES model. In contrast to renewable generators, instances of this group are fully dispatchable. They are able to increase and decrease their electrical output subject to their technical restrictions. The general structure of the power plant technology model with its main attributes is shown in figure 3.7. For each power plant type, such as lignite or GCC, a fleet structure defines the installed capacity and the number of blocks that form the fleet. Further, not every power plant instance within a fleet has the same technical properties. In that sense, the electrical efficiency is assumed to be most important. Therefore, an efficiency distribution of each fleet type is considered.

Based on the fleet structure a set of power plant instances that corresponds to the number of blocks is instantiated. Herein, each power plant block holds specific properties that can be distinguished into general data, operational restrictions and financial properties. Especially the marginal cost of power generation that determine the power plant's position in the merit order largely depend on the electrical efficiency and the CO₂ intensity. Since power plant technologies differ in their ability to dynamically change the electrical output, operational restrictions need to be taken into account. In that respect, especially the ramping limits are of major importance for the economic dispatch problem.

With a growing share of RES in power generation the relevance of storage technologies is growing. To cover this aspect, pumped hydro and battery storages are considered in the modeling approach. Both technologies are fully dispatchable and underlie restrictions regarding their

available storage capacity. Further, the electric charging and discharging power constitutes a limitation in their grid balancing potential. The average electric cycle efficiency takes into account the losses during the charge and discharge process and due to standing losses.

Using the above presented load and generation models the actual NES model implementation is done using the power system optimization toolbox PyPSA (Brown et al., 2018). A one node electrical grid model for the German electricity market is considered. Thereby, a copper plate power grid is assumed in which no transmission restrictions apply. All electric loads and generators are connected to the single grid node. Furthermore, no electric connection to neighboring countries is assumed to keep the modeling and computation effort at a reasonable level for this study.

Based on this model PyPSA forms an optimization problem that is solved towards minimum power generation cost within a given period of time. In this study a day-ahead approach was chosen which optimizes the upcoming 24 hours in a rolling horizon manner. Using the problem formulation a unit commitment is performed in a first step. Hereby, the optimization algorithm decides which generation unit will be in operation during the forecast period. Since all considered generators can either modulate their electrical output or can at least be curtailed, an optimal dispatch is calculated in a second step. This results in the actual electric output of each power generator within the NES.

For the analysis in this study the obtained power plant dispatch is of interest. Using the methodology presented in section 2.1.1 a marginal power plant is determined by the power plant dispatch for every time step of a year. As a consequence, the technical and economical properties of a particular power plant define the marginal cost and CO₂ intensity of power generation for a given time step. To validate the NES model a simulated marginal cost curve for the reference year 2017 is compared to the wholesale power price at the EEX (Bundesnetzagentur, 2019).

In order to assess the general offset of both curves the median (solid) and mean value (dotted) are calculated and can be seen in the left part of figure 3.8. Additionally, the interquartile range (IQR) and the 5% and 95% percentiles are calculated to evaluate the signal fluctuation.

Generally, both curves show good accordance in their mean and lower percentile values. A difference can be seen for the IQR and the upper percentile. In this upper part, model deviations occur in the power price for peak load delivery. Here, the applied modeling approach does not explicitly consider spot market transactions, and thus deviations between simulated and actual data can't be avoided. Nevertheless, for the considered purpose within this work, the level of accordance is sufficient.

The right part of the figure shows an exemplary week in April. It emphasizes, that besides the general offset and the fluctuation range, the price frequency shows good accordance as

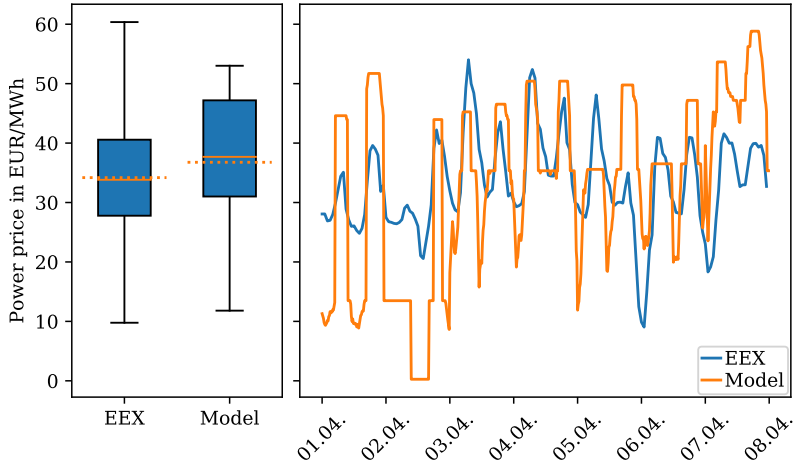


Figure 3.8: Comparison of power prices EEX vs. model. Annual statistics (left) and exemplary week in April (right).

well. This fact is especially important with respect to the utilization of operational flexibility provided by grid-driven CG systems.

3.2.2 Distribution power system model

The second part of the hybrid grid model concerns the DS. In general, the relevance of the DS state for the methodology in this study was already explained in section 2.1. However, the grid congestion power is a theoretical indicator which cannot be measured. Therefore, a model is necessary that is able to simulate the grid state under given boundary conditions. In contrast to the NES model, this part of the hybrid grid approach explicitly incorporates grid limitations. Besides the general modeling approach a distinct model implementation using a particular DS setup is needed. Figure 3.9 shows the schematic of the CIGRE LV suburban reference grid as in Schlösser (2019).

Based on the grid structure an electric grid model is instantiated in the power system analysis tool PYPOWER which is a Python implementation of MATPOWER (Zimmerman et al., 2011). In this DS model each node corresponds to the connection point of a residential building (SFH or MFH) to the grid. As shown in the toolchain overview 3.1, the main electric loads in a DS are loads from heating applications, EV charging and PV injection as well as other electric appliances. These building-specific loads operate on the grid connection points and are explicitly integrated into the annual PFC. During the step-wise PFC additionally the demand

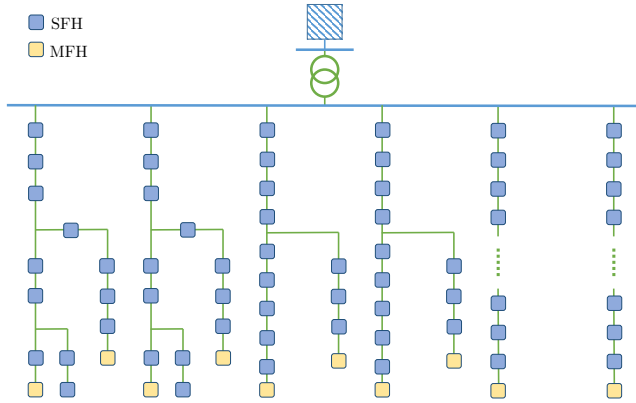


Figure 3.9: Schematic of corrected CIGRE reference suburban distribution grid according to Dickert et al. (2013).

for congestion power is determined following an approach developed in Schlösser (2019). As a result, the annual demand curve for congestion power is obtained which afterwards is used as a grid state indicator by the BES controls.

3.3 Environmental and behavioral input data

3.3.1 Weather

The weather data considered in models for BES and RES is an important factor in the presented methodology. On the one hand, the BES model that is used within the design optimization relies on information about the ambient temperature and the solar irradiation. On the other hand, the grid state models are affected by the environmental conditions to a great extend. Wind speeds in a given location determine the power output of a WEC. Further, the available solar irradiation is essential for the electricity generation by PV systems. Whereas WEC only influence the NES in the considered modeling approach, the feed-in from PV is relevant for both the NES and the DS. Since optimizations and the corresponding BPS should not only account for measured weather of a specific year and locations, the approach relies on generic TRY data (Deutscher Wetterdienst, 2017). This TRY weather data is available for arbitrary locations in Germany and represents the year 2015. It will be applied for the reference year 2017 and the 2030 projection scenarios.

With respect to the location, a distinction needs to be done depending on the model purpose. The BPS-based design optimization of the CG systems is performed for a single suburban

location (Frechen, Northrhine-Westphalia, Germany) in order to keep the computational effort in a reasonable range. Within this area the ambient temperature and solar irradiation influence the thermal energy demand of a building. As a consequence, the grid interaction and grid flexibility potential of electric HVAC technologies, such as HP and CG, depends on the considered weather data as well. In contrast to that, different representative German sub-locations were used in the NES context. Based on the TRY weather data of these sub-locations the grid state of the NES is obtained using the models presented before (cf. 3.2.1). However, in the BES and NES domain the supply and demand for electrical energy depend on the weather to a large extend. Electricity prices and the emission intensity are determined by the power generation mix and directly affect the performance of a CG system in the considered methodology. Therefore, the consistency of the used weather data in the NES and BES model is essential to perform a consistent design optimization.

3.3.2 User behavior

A further important factor in the energetic characteristics of a building are the residents living in it. In that sense, the thermal and electrical demand structure is highly correlated with the actual occupancy. For that reason, an occupancy-based approach for the generation of multiple energy-related input data is applied. Profiles that describe the occupancy of a single apartment for every time step of the year are created using a python tool (Schiefelbein et al., 2015). Within the tool an algorithm developed by Richardson et al. (2008) is used to calculate the actual profile considering the maximum number of residents. To obtain the occupancy profile of an entire MFH the number and size of its apartments is taken into account. With this information and the apartment-specific profiles the building's time-resolved occupancy can be determined. In a next step, the energetic demand curves for space heating, DHW and electric appliances are calculated using the occupancy.

Further, the desired room temperature and the ventilation rate are important and can be influenced by the user. In the conducted thermal demand calculations a set room temperature of 20 °C is assumed. Furthermore, a ventilation rate ranging from 0 to 1.0 h⁻¹ is added to a constant infiltration rate of 0.2 h⁻¹ depending on the relative occupancy. As a result, the overall air exchange rate of all considered MFH is between 0.2 h⁻¹ for an empty building and 1.2 h⁻¹ for a fully occupied one.

The thermal energy demand for the preparation of DHW depends on the user behavior as well. On the one hand the tapped water volume and on the other hand the applicable temperature level of the DHW are relevant. Within this study, an average DHW demand of 64 l per day and person at 45 °C is assumed. However, due to the stochastic nature of the used approach the actual daily demand varies. In addition to the DHW demand, the electricity demand of household appliances, such as lighting and other electric appliances, is modeled based on the presented occupancy profile. In contrast to DHW, the influence of the electric appliances is

two-fold. Firstly, the electrical grid interaction due to power demand directly affects the DS. Secondly, the internal gains provided by dissipation in the appliance devices is able to reduce space heating demand of a building. Especially for MFH with a high occupant density this effect can lead to SH demand reductions.

3.4 Economic input data

One of the major goal of this study is to analyze the CO₂ abatement cost of grid-driven CG systems and their role in a future power market. To provide an insight on these aspects, a thorough economic investigation is needed in addition to the technical considerations. Further, the representation of a dynamic grid context uses a simplified power market which requires assumptions on its economics. For both above fields reasonable assumptions need to be made. A recently introduced factor in this respect is the cost for CO₂ emission. The Emission Trading System (ETS) has been in place for several years already in the European Union and is applicable for power plants. However, within the economic assessment of this study, responsibility to purchase CO₂ emission allowances applies for BES as well. According to the considered scenario a price between 6.42 €/t and 50 €/t is assumed. In the following two sections specific economic input data for BES and the NES are described.

3.4.1 Building energy system

The performance assessment of CG systems is done using an enviroeconomic approach, which considers both the environmental and economic performance. To take into account the technologies' economics, the net present value (NPV) method is applied as already presented in section 2.2.2. The determining parameters in this approach are the imputed interest rate i and the period under review T . Since the main interest rates stay in a very low range for several years already, an imputed interest rate of $i = 3\%$ p.a. is assumed. The period under review is set to $T = 20$ a, which can often be found when analyzing the economic viability of BES.

For more sophisticated HVAC systems like HP and CG the capital expenses often are a crucial element of cost. They mainly depend on the components' capacities. The necessary investment of different technologies can be taken into account by applying specific investment curves. A turnkey CG system can be calculated using investment curves for each component, i.e. CG device, TES and installation cost. A German study on CG systems provides insight on the device cost of market available products (ASUE e.V., 2014). With availability of CG devices using different fuel types it enables the determination of specific investments in relation to the electrical output. Further, investment curves for different electrical capacity classes are available. Within these classes the smaller CG devices using natural gas range from a electrical capacity of 0 to 10 kW:

$$I_{CG} = \underbrace{9585 \cdot P_{el,CG}^{-0.542}}_{\text{specific investment}} \cdot P_{el,CG} = 9585 \cdot P_{el,CG}^{0.458} \quad (3.6)$$

Devices from this power range are traditionally suitable for SFH or small MFH. The next higher class ranges from 10 to 100 kW and is expected to be most relevant for grid-driven applications in MFH as in this study:

$$I_{CG} = \underbrace{5438 \cdot P_{el,CG}^{-0.351}}_{\text{specific investment}} \cdot P_{el,CG} = 5438 \cdot P_{el,CG}^{0.649} \quad (3.7)$$

In addition to the aforementioned capacity ranges very large CG systems can make sense in large, non-retrofitted MFH. With respect to that, the investment for CG units ranging from 100 to 1000 kW of electrical output are determined as follows:

$$I_{CG} = \underbrace{4907 \cdot P_{el,CG}^{-0.352}}_{\text{specific investment}} \cdot P_{el,CG} = 4907 \cdot P_{el,CG}^{0.648} \quad (3.8)$$

From the above equations it can be noticed that the specific investment decreases with increasing electrical output of the devices. This characteristic of the investment curve is an important aspect and enables the economically beneficial installation of large CG units under suitable boundary conditions. The resulting absolute investment curves for CG units and GB are depicted in figure 3.10.

In addition to the equipment cost the cost for installation and commissioning of BES need to be considered. These cost elements can be expressed in relation to the equipment cost and depend on the cogenerator sizing as well. Table 3.1 shows the applicable ratios for the most relevant electrical capacities of up to 350 kW.

Table 3.1: Relative cost for installation and commissioning.

$P_{el,CG}$ [kW]	relative installation cost
0..3	0.59
3..10	0.51
10..100	0.45
100..350	0.51

The CG considered in this work are always accompanied by a TES to provide flexibility. Therefore, the capital expenses related to the investment into the TES directly affect the economic performance of the CG system. Again, capacity dependent investment curves are applied to take this cost element into account. For TES volumes in the range of several m³ a

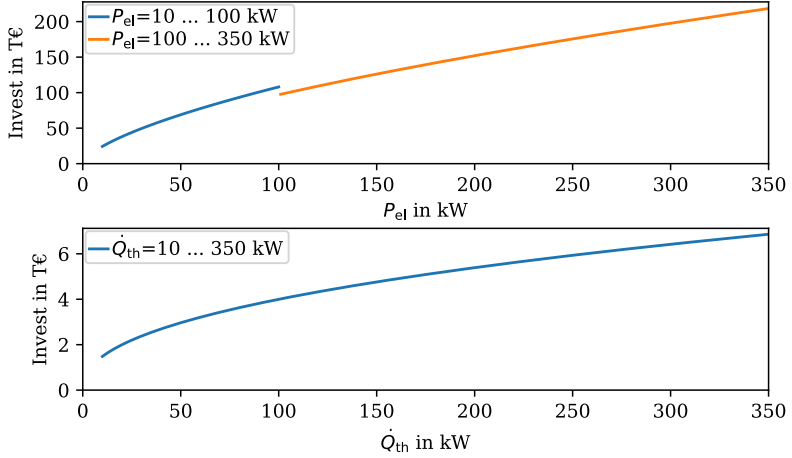


Figure 3.10: Absolute investment curves for the relevant capacity classes of CG units and GB.

linear investment curve is applied which covers all the considered cases in this study (Spieker and Tsatsaronis, 2011).

$$I_{\text{TES}} = 500 + 1450 \cdot V_{\text{TES}} \quad (3.9)$$

The economic assessment within this work relies on the comparison of a CG system with a reference system. Based on this comparison the CO_2 abatement cost are calculated. Just like CG systems however, an investment into a reference system is necessary when replacing or retrofitting the BES of a MFH. To enable a fair comparison the investment curve according to 3.10 is applied for a reference GB. The investment curve is based on manufacturer data of different GB sizes (Buderus, 2017). Since the storage technology of the reference system does not differ from the CG system the investment for a reference TES is also described by equation 3.9.

$$I_{\text{GB}} = 549.29 \cdot \dot{Q}_{\text{GB}}^{-0.369} \cdot \dot{Q}_{\text{GB}} = 549.29 \cdot \dot{Q}_{\text{GB}}^{0.431} \quad (3.10)$$

Expenses for the operation play an important role in the assessment of CG systems. As observed for other heating technologies the fuel cost are most important in this respect. Gas prices show large variations depending on the annual consumption. Whereas power plants procure natural gas for net prices in a range of 20 to 30 €/MWh, private households normally

pay more than 50 €/MWh. With respect to that a net gas price of 51 €/MWh is assumed which corresponds to the reference year 2017 (Bundesnetzagentur, 2018a).

However, with an electricity producing technology like CG also positive cash flows exist that need to be taken into account. In the considered grid-driven CG setup no fixed feed-in tariff is applied. Instead, the monetary value of produced power is defined by the wholesale power price within the NES as presented in chapter 2. The only fixed positive cash flow originates from avoided electricity grid usage. This credit is accounted for since distributed generators do not use the transmission grid but only the DS (Bundesnetzagentur, 2015). In 2017 the grid usage fee for private households was set to 0.0699 €/kWh (Bundesnetzagentur, 2020). However, in recent years a tightening in regulations for the granting of a avoided grid usage bonus is observed (Bundesministerium für Wirtschaft und Energie, 2017). The main argument is that distributed generation only reduces grid reinforcements in specific applications. To account for this fact only the cost that arise on the LV and MV level of the electricity network are considered. This leads to the assumption of a 50 % reduced average bonus of 0.035 €/kWh.

In contrast to GB or HP systems, where expenses for maintenance are negligible, they constitute a significant element of cost for CG. The main reason is the higher system complexity and the inevitable wear of combustion engine components and fluids. To consider these cost elements properly different maintenance price curves for particular device capacities are used (ASUE e.V., 2014). Since engine cycling which largely influences its wear is explicitly considered in the presented methodology, the revision-related element of cost from ASUE e.V. (2014) is isolated by multiplication with 0.8 as shown in 3.11 (ASUE e.V., 2011). The pure maintenance cost can be obtained by multiplying the following price with the electricity generation of the CG system.

$$p_{m,CG} = \begin{cases} 3.2619 \cdot P_{el,CG}^{-0.1866} \cdot 0.8 & , P_{el,CG} \leq 10 \text{ kW} \\ 6.6626 \cdot P_{el,CG}^{-0.25} \cdot 0.8 & , 10 \text{ kW} < P_{el,CG} \leq 100 \text{ kW} \\ 6.2728 \cdot P_{el,CG}^{-0.283} \cdot 0.8 & , 100 \text{ kW} < P_{el,CG} \leq 1000 \text{ kW} \end{cases} \quad (3.11)$$

In addition to ordinary maintenance CG systems require occasional engine revisions. The prices for a full revision depends on the electrical capacity and is taken from ASUE e.V. (2014).

$$p_{rev,CG} = 832.45 \cdot P_{el,CG}^{-0.2808} \cdot P_{el,CG} = 832.45 \cdot P_{el,CG}^{0.7192} \quad (3.12)$$

3.4.2 National energy system

The current state of the NES is one of the core components in the presented CG setup. It is mostly determined by the underlying market economics, that are expressed using a power

market model. To calculate a time-resolved power plant dispatch some economic figures are needed and assumptions need to be made. In contrast to the NPV considerations made for the BES, capital expenses do not affect the power market economics. Instead, the wholesale power price is only determined by the merit-order of power plants which solely follows the operational cost of power generation. As for BES, fuel cost are a major element of cost in power generation. These cost largely differ depending on the considered power plant technology and its fuel type. For the power plant types that are considered in the presented NES model, table 3.2 shows the fuel prices that are assumed (Bertsch et al., 2016)(Statista, 2020).

Table 3.2: Net fuel prices for conventional power plants.

Fuel type	p_{fuel} [€/MWh]
Hard coal	11.88
Lignite	1.44
Uranium	3.88
Natural gas	23.58
Oil	55.65

Besides, further operational cost components need to be considered to properly model the power plant dispatching. Most important in that sense are the cycling and operation and maintenance cost which are shown in table 3.3.

Table 3.3: Operation and maintenance cost per power plant type.

Technology	c_{cyc} [€/MW]	c_{m} [€/MWh]
Hard coal	251	2.0
Lignite	251	2.0
Nuclear	663	0.0
GOC	44	0.7
GCC	44	0.7
Misc	44	0.7

3.5 Technical input data

From a technical perspective different assumptions on the input data need to be made as well. These input data mainly refer to the properties of the BES comprising the building envelope and the HVAC system that provides the supply of thermal and electrical energy. In addition to that, technical properties of the power plant portfolio considered in the NES model are presented in the following. Both above aspects ultimately affect the CG system's performance that is under investigation in this work.

Table 3.4: Overview on investigated building/occupant combinations.

Building ID	floor area [m ²]	retrofit state [-]	occupant area [m ² /occ]	no. occupants [-]	no. apartments [-]
1	500	original	40	13	7
2	500	usual	40	13	7
3	1000	original	40	25	13
4	1000	usual	40	25	13
5	500	original	60	9	5
6	500	usual	60	9	5
7	1000	original	60	17	9
8	1000	usual	60	17	9
9	500	original	20	25	13
10	500	usual	20	25	13
11	1000	original	20	50	25
12	1000	usual	20	50	25

3.5.1 Building energy system

As already addressed in section 3.1 the parameterization of the building models follows an archetype approach presented by Loga et al. (2016). Nevertheless, the actual building setups that are considered in this study need to be explained briefly. For that purpose, table 3.4 gives a full overview on the investigated combinations of buildings and occupant densities.

The efficiency of a CG device is an indicative measure to estimate its performance. When considering grid-driven systems, specifically the electrical efficiency plays an exceptional role and it is one of the key performance factors for CG. It depends mainly on the electrical capacity and increases with larger unit sizes. When comparing similar CG types the overall fuel efficiency shows only minor variations over the device's capacity. It is therefore assumed to be $\omega = 0.85$. In consequence, a decreasing thermal efficiency $\eta_{th, CG}$ can be observed with increasing capacity. The rated electrical efficiency that is applicable for the design working point can be expressed as follows (Gelegenis and Mavrotas, 2017):

$$\eta_{el, rat} = 0.0252 \cdot \ln(P_{el, CG}) + 0.226 \quad (3.13)$$

The rated thermal efficiency consequently results as:

$$\eta_{th, rat} = \omega - \eta_{el, rat} = \omega - 0.0252 \cdot \ln(P_{el, CG}) - 0.226 \quad (3.14)$$

In addition to the efficiency the utilized NES state signal that is fed into the level-0 controller of the CG system is an essential input. The signals that are obtained using the methodology and models presented in sections 2.2.4 and 3.2.1 can be of mixed or marginal type. An analysis on the effect that both signal types have on CG systems is also part of this work. Therefore, each building setup shown in table 3.4 is either combined with a mixed-type or marginal-type NES signal.

3.5.2 National energy system

The NES can be described as a fleet of power plants. Information on the fleet composition for different scenarios is already given in section 3.2.1. Beyond the power plant types and capacities the operational characteristics of each plant within the NES have significant impact on the resulting power plant dispatch. Especially modulation and ramping limits, e.g. of lignite power plants, are able to drastically affect the utilization of pumped hydro storage capacities and RES curtailment since power generation cannot be reduced any further or fast enough. An overview on the considered operational restrictions for specific technologies is given in table 3.5. The overview shows that nuclear and lignite power plants have comparably high modulation limits and are not able to follow dynamic residual load changes. Looking at gas-fired power plants (GOC or GCC) clearly reveals their superior abilities in that sense. These effects are explicitly considered in the power plant dispatch model.

Similarly to BES the electrical efficiencies of power plants within a NES have a strong influence on the CO₂ emission intensity and the wholesale power prices. Further, these efficiencies underlie a certain deviation. Table 3.6 shows the efficiency related input data that is used to formulate and solve the power plant dispatching problem (van den Bergh and Delarue, 2015). Here, the electrical efficiency corresponds to the mean value of a given power plant technology. The relative deviation is then used to form a plant fleet with equally distributed electrical efficiencies.

However, not only the electrical efficiency but rather the CO₂ emission linked to specific fuels determine the environmental performance of power plants and thereby the CO₂ emission intensity of a NES. In table 3.7 an overview on the considered power plant fuels is given.

Table 3.5: Operational characteristics of conventional power generation portfolio (van den Bergh and Delarue, 2015)(Göransson et al., 2017).

Technology	$P_{\min, \text{rel}}$ [-]	$\Delta P_{\text{start, rel}}$ [h ⁻¹]	$\Delta P_{\text{stop, rel}}$ [h ⁻¹]	$\Delta P_{\text{up, rel}}$ [h ⁻¹]	$\Delta P_{\text{down, rel}}$ [h ⁻¹]	$t_{\text{up, min}}$ [h]	$t_{\text{down, min}}$ [h]
Hard coal	0.5	0.33	0.5	1.0	2.0	5.0	6.5
Lignite	0.5	0.2	0.33	1.0	2.0	5.0	6.5
Nuclear	0.7	0.2	0.33	1.0	2.0	12.0	24.0
GOC	0.2	4.0	4.0	4.0	4.0	0.5	0.5
GCC	0.2	1.0	2.0	1.0	2.0	3.0	3.0
Misc	0.2	4.0	4.0	4.0	4.0	0.5	0.5

Table 3.6: Performance characteristics of generation portfolio (van den Bergh and Delarue, 2015)(Göransson et al., 2017).

Technology	η_{el} [-]	$\Delta\eta_{\text{el, rel}}$ [-]
Hard coal	0.4	∓ 0.1
Lignite	0.4	∓ 0.1
Nuclear	0.33	∓ 0.05
GOC	0.35	∓ 0.15
GCC	0.5	∓ 0.15
Misc	0.3	∓ 0.2

Table 3.7: CO₂ emission intensity of different fuels in relation to lower heating value (Icha and Kuhs, 2017).

Fuel type	f_{CO_2} [t/(MWh)]
Hard coal	0.335
Lignite	0.407
Nuclear	0.04
Natural gas	0.202
Oil	0.266

4 Results of design optimization

The presented enviroeconomic assessment and design optimization methodology is applied to a set of different building setups and energetic context scenarios. For that purpose, 216 scenario combinations are considered where each is optimized towards CO₂ abatement cost and congestion mitigation in the electric DS. A single optimization run consists of 1'300 annual BPS. Each run is repeated ten times to obtain robust results which leads to over 2.8 million simulations within this study. This chapter addresses the research questions that are presented in the beginning of this work.

The first section gives an introduction to the optimization results and explains how these are interpreted. Some general information on the dimensionless system characteristics are briefly presented. This part is followed by an analysis of the effect that different buildings and power systems have on the performance and optimal design of CG systems. Regarding the building's effect, the floor area, retrofit state and occupant density are considered. In addition, the influence of the NES structure and electrification level in the DS is addressed. The mixed and marginal grid state concept are compared to each other with respect to the operation and assessment of CG systems. Following this approach the general applicability of grid-driven CG systems in different context is assessed. An overview on the achievable enviroeconomic performance of the considered CG systems is given.

In a next step the performance of optimized grid-driven CG systems is compared to heat-driven systems. Thus, further insight on the relevance of unit sizing and operation is gained. Additionally, the performance of CG systems that are equipped with a RC unit is presented. The last section of this chapter addresses the role of CG in comparison to conventional power plants. Here, the focus is on economic considerations where the levelized cost of electricity (LCOE) are concerned. This part is concluded with a financial assessment of the grid service that is offered to the DS. For that purpose the marginal cost for congestion mitigation are presented.

4.1 Introduction to optimization results

The optimization algorithm is applied to BES consisting of different building envelopes and occupant densities. As a consequence, these cases vary in peak heat load and overall thermal demand for SH and DHW. Since comparability among different cases is needed, dimensionless quantities for the thermal output of the CG unit and the thermal storage capacity of the TES

are introduced. These dimensionless characteristics follow the work of Stinner et al. (2016). According to this approach, the thermal output of the CG device is expressed in relation to the design peak load of a given building.

$$\alpha_{\text{th}} = \frac{\dot{Q}_{\text{CG,nom}}}{\dot{Q}_{\text{b,nom}}} \quad (4.1)$$

Accordingly, the dimensionless storage capacity β_{th} following equation 4.4 is expressed using the average daily heat demand of a building as defined in 4.2 by putting the annual heat demand in relation to the number days per year n_{d} . The absolute thermal capacity is calculated using equation 4.3. Herein, a usable temperature spread of $\Delta T_{\text{nom}} = 40 \text{ }^{\circ}\text{C}$ is assumed for both the reference and the CG system.

$$Q_{\text{b,d}} = \frac{Q_{\text{DHW}} + Q_{\text{SH}}}{n_{\text{d}}} \quad (4.2)$$

$$Q_{\text{TES,nom}} = V_{\text{TES}} \cdot \rho_{\text{w}} \cdot c_{\text{w}} \cdot \Delta T_{\text{nom}} \quad (4.3)$$

$$\beta_{\text{th}} = \frac{Q_{\text{TES,nom}}}{Q_{\text{b,d}}} \quad (4.4)$$

By applying these dimensionless characteristics general implications for a reasonable CG design are identified in the following analyses. An exemplary optimization result is shown in figure 4.1 for a non-retrofit 1'000 m² MFH. The corresponding optimization case considers a DS electrification level of 50 % in scenario A2030. In the upper part of the figure the performance of all final Pareto individuals that are obtained during ten optimization runs are depicted. The performance value accounts for the achieved CO₂ abatement cost AC and the residual demand for congestion energy $\bar{w}_{\text{c,res}}$ within the local DS. From these different Pareto sets the best performing individuals are chosen. They form the best solution that is found using the presented GA with its specific setup and are indicated in black. Nevertheless, GA naturally cannot guarantee the identification of a true Pareto front, but are able to find a purposeful best Pareto front, which is close to the true one.

Below, design parameters that correspond to the above Pareto front are presented. Each individual from the Pareto set is defined by its unit capacity α_{th} , storage size β_{th} , threshold level for forced operation λ_{force} and controller time horizon t_{hor} , and is found at the particular CO₂ abatement cost level. Hence, a clear mapping of each Pareto individual to its characteristic

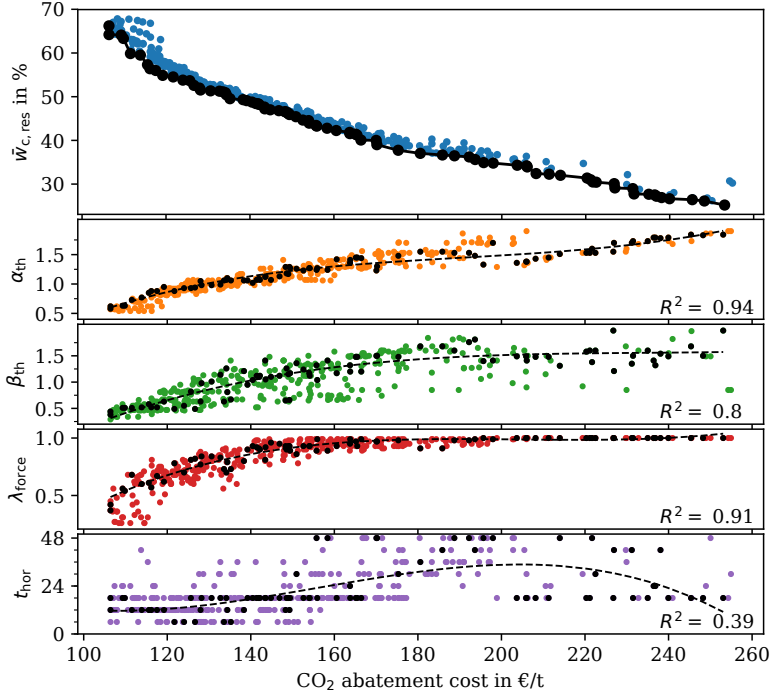


Figure 4.1: Exemplary result of a 1'000 m² non-retrofit MFH in a 50 % DS electrification and A2030 NES scenario. The above curve shows the performance of each analyzed individual. Below, the corresponding design parameters are depicted.

design parameters exists. Based on this mapping, a comprehension of the effects that certain parameter values have on the CG system's performance is gained.

As in the Pareto front plot, the results of all ten optimization runs are depicted. The design parameter sets that belong to the best Pareto set are indicated in black as well. A closer look at the Pareto front reveals a certain amount of variation among different optimization runs. These variations inevitably occur when using a GA due to its stochastic nature. In contrast to performance points of the Pareto front the design parameter values partially show a significant variance. The aforementioned effect is linked to the stochastic behavior of the GA as well. Nevertheless, differences between individual design parameters are observed. Especially the thermal storage capacity of the TES and the forecast horizon show a notable level of variance. The explanation is their rather indirect effect on the CG system performance. A larger CG unit size directly affects the supplied congestion energy during a local grid event. In contrast,

a larger TES volume does not necessarily increase the congestion energy during that same grid event. One reason is, that a congestion situation might not last long enough for the TES capacity increase to take effect.

Nevertheless, in most optimization cases a clear trend can be identified for each design parameter. To describe these trends with indicative design curves, functional regressions are calculated that fit the found optimization results in a most suitable way. For that purpose, a third-degree polynomial fit is used that minimizes the squared error. The achieved coefficient of determination R^2 for each optimization parameter is shown in the figure. In accordance to the aforementioned effect of larger deviations for β_{th} and t_{hor} the corresponding regression curves show lower R -values. Concerning the forecast horizon t_{hor} , however, the coefficient of determination is largely influenced by its comparably coarse discretization of $\Delta t_{hor} = 6$ h. Nevertheless, the effect of the forecast horizon on the actual performance of the considered CG systems is only weak. Therefore, it is not further considered in the following analyses. In comparison, a good coefficient of determination is obtained for the thermal output α_{th} and the controller threshold level λ_{force} .

The optimization in this work covers a large set of different scenario combinations which cannot be presented individually. In the following three sections, individual system parameters, such as the NES scenario, will be kept unchanged while varying others. Thus, general effects that refer to a variable system parameter are further investigated. Nevertheless, a consolidated overview of all Pareto fronts that are considered in the simulation campaign is presented in figures B.1 to B.12.

4.2 Effect of the building

In this section the fixed scenario parameter is the power system which considers medium electrification level of $\xi_{el} = 50$ % in the NES scenario A2030. However, the retrofit level, floor area and occupant density vary. Hence, the effect of the BES on the CG performance and the corresponding implications on the CG system design are addressed.

4.2.1 Building envelope and size

Figure 4.2 depicts the performance depending on the building size and retrofit level. Four combinations are considered using a marginal grid state signal. The presented buildings show significant differences in performance for both optimization targets. Herein, large non-retrofit buildings achieve the best performance, whereas small retrofit buildings perform worst. In fact, the difference in CO₂ abatement cost lies around a factor of three between the 500 m² retrofit building and the 1'000 m² original one. In contrast, the 500 m² original and 1'000 m² retrofit building perform almost equal. Nevertheless, all presented systems are competitive in

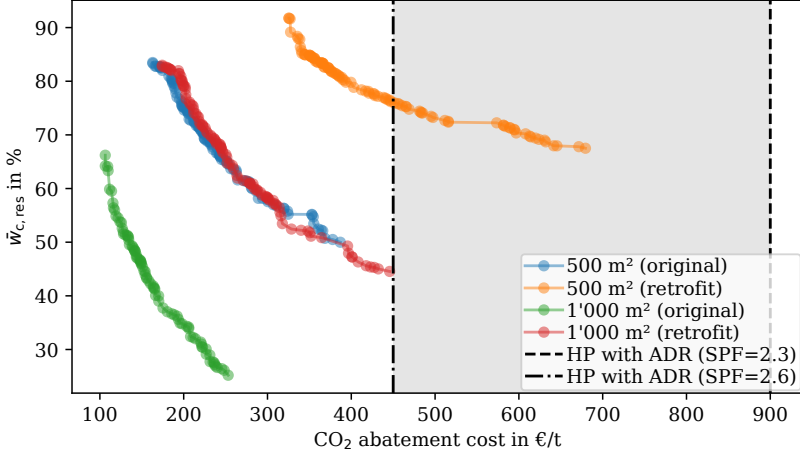


Figure 4.2: Performance comparison of BES for different floor areas and insulation standards in a given surrounding energy system ($\xi_{el} = 50\%$, A2030, marginal).

comparison to the HP system using active demand response (ADR) according to a study of Patteeuw et al. (2015).

With respect to a reasonable congestion mitigation potential the slope of the curve is of interest. Generally, it is observed that larger buildings achieve better values for the reduction of grid congestion over the entire Pareto front. Besides, the slope of the Pareto front is steeper for large buildings and very flat for small retrofit ones. This fact implies that congestion management causes relatively larger additional cost for small buildings. Furthermore, it deteriorates CO₂ abatement cost.

Implications of the building choice on the design of a grid-driven CG system are presented in figure 4.3. Regarding the size of the CG unit and the TES both medium performing systems are similar. However, significant differences are found for the 500 m² retrofit and the 1'000 m² building equipped with original insulation. Specifically, the former needs a larger CG unit accompanied by a large TES. This effect can already be observed for a CO₂ focused system with low congestion mitigation potential. An explanation can be found in the very low SH to DHW ratio γ_{th} . Additionally, smaller buildings usually show a lower simultaneity factor in DHW demand. Hence, the peak heat demands within a building play a more important role, which leads to a larger dimensioning of the CG unit and TES size. Equipped with an exceptionally large TES, the CG unit in the 500 m² retrofit building is able to exploit less but more favorable phases

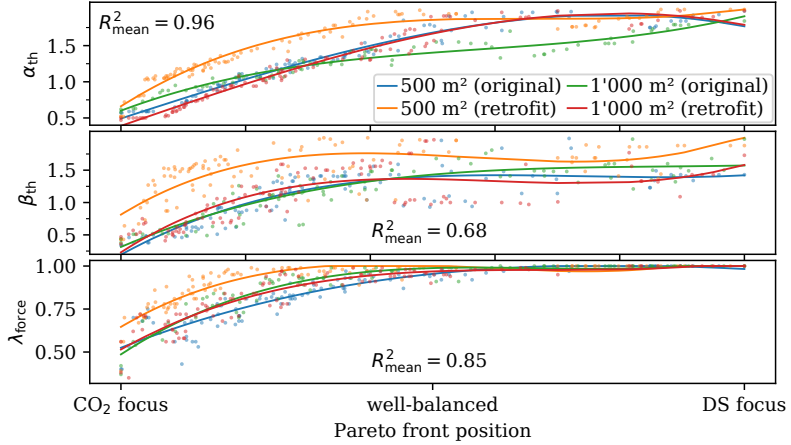


Figure 4.3: Design comparison of BES for different floor areas and insulation standards in a given surrounding energy system ($\xi_{el} = 50\%$, A2030, marginal).

of high enviroeconomic power values. Consequently, a higher controller threshold λ_{force} can be used.

For the sizing of the CG unit in a 1'000 m² MFH with original retrofit a different picture is observed. Here, the optimization obtained a rather flat curve which is due to a comparably large value for ξ_{th} . In this case, the heat demand and the nominal heat load of the building is mainly determined by SH. This design effect leads to a smooth CG operation and feed of electricity to the grid in the heating season. Hence, load congestion situations in the local DS, that preferably occur during winter, are naturally mitigated without the need for additional electrical capacity of the considered CG system. The steep slope of the Pareto front for this particular case further emphasizes this fact.

To achieve a maximum impact on possible grid congestion, all the presented BES utilize CG unit sizes that are close to the maximum of $\alpha_{th} = 2$. The downside of this oversize arises in high CO₂ abatement cost. However, the dimensioning of the TES mostly stays below its maximum. Instead, the highest values turn out to be around $\beta_{th} = 1.5$. An exception to the rule states the 500 m² retrofit building which shows an offset over the entire TES sizing curve. Starting from values around $\lambda_{force} = 0.5$ the controller threshold shows an early convergence to the maximum value $\lambda_{force} = 1.0$ in the middle of the curve for all BES. This is due to comparably lower storage capacity relative to the installed CG unit power of the analyzed systems. In fact, the capacity of the TES shows a positive offset to the other curves, however,

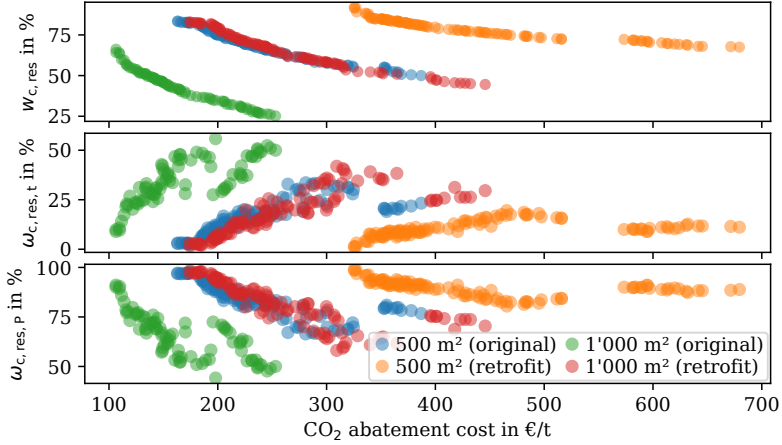


Figure 4.4: Residual congestion shares of BES for different floor areas and insulation standards in a given surrounding energy system ($\xi_{el} = 50 \%$, A2030, marginal).

the gap that opens between the α_{th} -curves overcompensates the capacity effect in the first half of the curve.

Nevertheless, a precise indication to which extent the BES choice affects the suitable forecast horizon is not possible based on the obtained results. A lower variance of the results and thereby higher coefficient of determination of the regression curve would be necessary. As a consequence, the other design parameters are considered to be more relevant for the design of a grid-driven CG system.

The observation that larger non-retrofit buildings perform better than others is further elaborated in the following. With respect to the choice of α_{th} and β_{th} the different nominal heat loads of buildings are an important factor. In fact, it can lead to significant differences in the absolute sizing of a CG system and thereby directly affect the economics and power flexibility of a CG system.

The latter is analyzed using figure 4.4. In the upper part it shows the general performance of the optimized BES that were already addressed above. Below, the residual demand for congestion energy $w_{c, res}$ is split into two categories. The first category $\omega_{c, res, t}$ describes the share of grid congestion energy that is not mitigated due to idleness of the CG unit. Complementary, the second category $\omega_{c, res, p}$ considers the share of congestion energy that is not covered due to a lack of available electrical capacity of the CG unit.

A comparison of the scatter fields of different buildings reveals that the 1'000 m² original building time-wise misses the supply of congestion power to a greater extent than the other systems. In fact, the remaining CG systems are able to address almost every congestion situation from a temporal perspective. They only lack the necessary power flexibility to entirely mitigate those events. As expected, the BES of the large non-retrofit building is less limited in congestion management by its electrical capacity. As already explained above, an increased α_{th} and β_{th} leads to an improvement of the congestion mitigation potential. However, this capacity increase takes stronger effect for the large non-retrofit building where a significant shift from temporal to power flexibility can be seen. At the same time, the CO₂ abatement cost increase only moderately. In contrast to that, the 500 m² retrofit building is hardly able to realize that shift without drastically increasing the cost for CO₂ abatement.

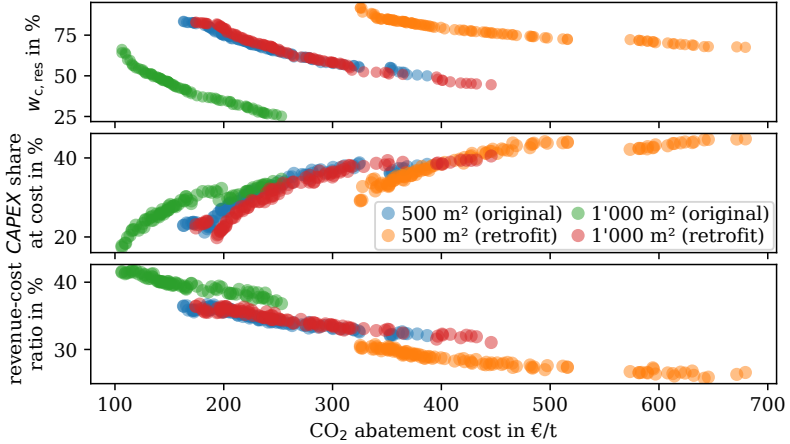


Figure 4.5: Cash flow structure of BES for different floor areas and insulation standards in a given surrounding energy system ($\xi_{el} = 50\%$, A2030, marginal).

Besides these technical aspects the economic reasons for the obtained results need to be analyzed as well. Figure 4.5 shows the cash flow structure of the above considered buildings. Among different cash flow origins the investment-related CAPEX and the operation-related revenues from power export to the grid are most important with respect to the CG system sizing. The CAPEX share at full cost indicates the advantage that larger CG systems have over smaller ones due to their favorable specific investment. For the best performing 1'000 m² building the CAPEX share is as low as 18 % of the overall annualized cost. In accordance with that, its revenues to full cost ratio is significantly higher than for CG systems with smaller absolute capacities. In fact, the improved grid-driven operation towards high enviroeconomic

values of power has a significantly larger leverage in such buildings compared to smaller or renovated ones.

The same analysis using a mix grid state signal is conducted as well. The results can be found in figures B.13 to B.16 of the appendix and appear in the same order as the ones elaborated above. Generally, in a mixed assessment approach the CO₂ abatement cost are significantly higher. Regarding the implications of the BES on the optimal design mostly similar results are found. Especially the notable oversizing of the MFH with the lowest thermal energy demand can be identified as well. However, some of the aforementioned effects differ. Specifically, all considered buildings show larger TES already with a focus on CO₂. The main reason can be found in the mixed enviroeconomic value of power. Due to the large amount of RES in power generation the CO₂ intensity has a comparably low mean value with only moderate fluctuations (cf. figure 2.25). This leads to only minor exploitable signal peaks that are sparse and limited in duration. To partially overcome these limiting factors the CG systems need to encounter with comparably larger CG units and larger TES volumes. The first measure leads to an increased power flexibility to better address grid congestions. The second measure provides a larger temporal flexibility to fully exploit sparse signal peaks. However, these increased capacities come at higher cost due to the additional investment.

4.2.2 Occupant density

Besides the building size and the retrofit level further influencing factors on the performance are found. Among those, the occupant behavior is of major importance. In this study the occupant effect is considered using the occupant density. It is expressed by the floor area per occupant A_{occ} and varies between 20 and 60 m². The variation effect of A_{occ} is exemplary depicted in figure 4.6 for a retrofit and non-retrofit building.

Retrofitting of buildings increases the CO₂ abatement cost and simultaneously reduces the supply of congestion energy. In addition to that, a clear effect of the occupant density is observed in both presented retrofit cases. In this respect, lower densities lead to lower CO₂ abatement cost, where the largest difference is found between specific floor areas of 20 and 40 m². Further the Pareto front belonging to the highest density of 60 m² shows higher maximum potential for congestion management. A downside in this case is the large increase in CO₂ abatement cost though.

Comparable to the building size and its envelop the occupant density has implications on the CG system design. These can be identified based on the sizing curves that result from the GA and are presented in figure 4.7. In this sense, a stronger effect for retrofit buildings is expected since the thermal energy demand for SH is generally lower. Therefore, a variation of the occupant density has a strong leverage in two ways. First, internal gains have a reducing effect on the SH demand and its peak heat load during the heating season. Second, the DHW

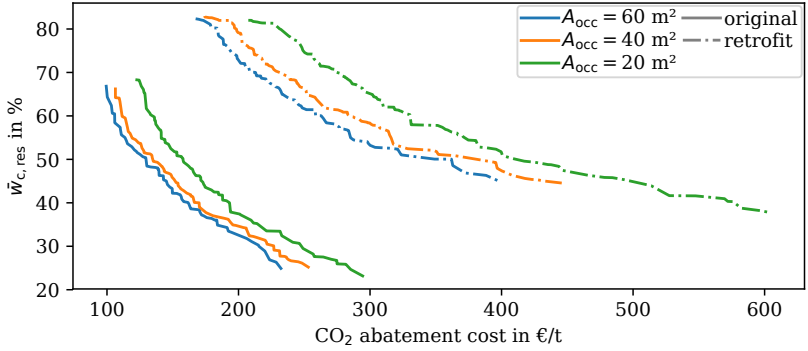


Figure 4.6: Performance comparison of different occupant floor areas in a 1'000 m² MFH located in a given surrounding energy system ($\xi_{el} = 50\%$, A2030, marginal).

demand has an increasing effect on the thermal energy and power demand for the entire year. The total heat demand is only slightly affected by the occupant density. Instead, the periodic thermal peak loads induced by an increased DHW demand overcompensate the internal gains effect. These peak loads need to be covered either by an increased output of the CG unit or a larger TES volume. Figure 4.7 shows that for low CO₂ abatement cost the absolute thermal output of the CG unit is comparable to other cases. As a consequence, the TES size is increased by the optimization, which in turn leads to a higher investment.

The design impact on the operational characteristics are presented in figure 4.8. It shows, that the additional storage capacity of the 20 m² case is mainly used to improve the time-wise congestion mitigation. A further observation is that high occupant densities and the corresponding DHW demand extend the CG operation beyond the heating season which improves the provision of grid flexibility in summer as well. To exploit these limited phases best, however, a large unit size needs to be chosen. Consequently, this further increases the investment and thereby negatively affects the CO₂ abatement cost.

The optimization results of the presented occupant densities lead to smooth Pareto fronts that migrate from low CO₂ abatement cost with low congestion mitigation potential towards comparably high cost and congestion energy supply. However, with very high CO₂ abatement cost a switch from an NES to a DS focus appears. It is indicated by a step in the $w_{c,res,P}$ and $w_{c,res,t}$ scatter fields which is also observed for the forced operation timeshares. These are depicted in figure 4.9. The reason for this step is a sudden increase of the temporal flexibility of the CG system. This increase is achieved by reducing the thermal output of the CG unit and a larger TES volume. It is found for other scenarios as well and originates from the CG unit size limitation of $\alpha_{th} = 2$. Due to this limitation no further improvement in congestion mitigation can be achieved. As a consequence, any further improvement needs to come from

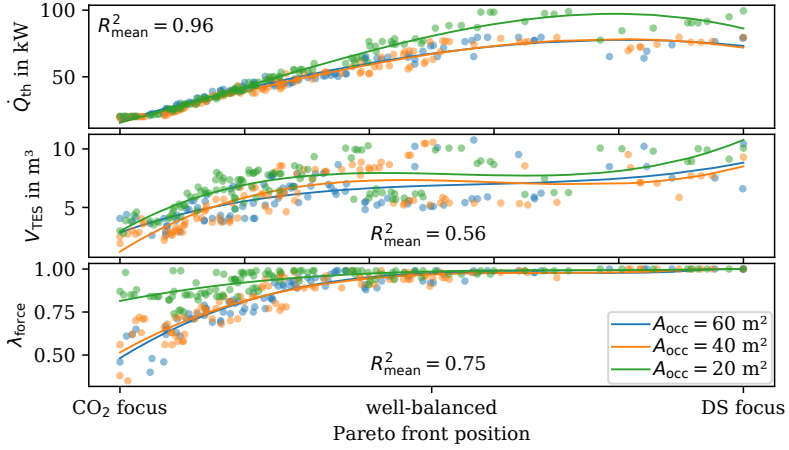


Figure 4.7: Design comparison for different occupant floor areas assuming in a given surrounding energy system ($\xi_{el} = 50 \%$, A2030, marginal).

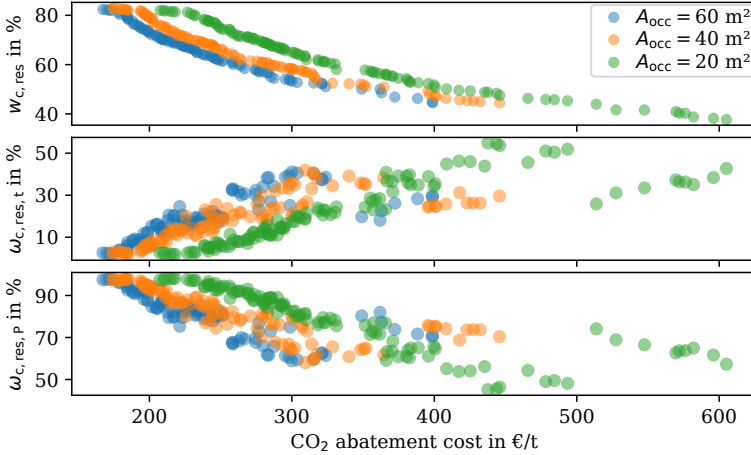


Figure 4.8: Origin of residual congestion energy for different occupant floor areas in a given surrounding energy system ($\xi_{el} = 50 \%$, A2030, marginal).

an extended temporal flexibility. Yet, the improved congestion management abilities come at

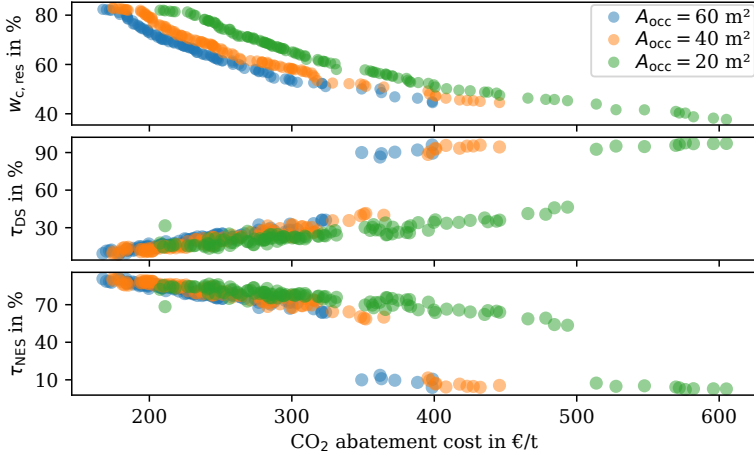


Figure 4.9: Operational system focus for different occupant floor areas of a 1'000 m² MFH located in a given surrounding energy system ($\xi_{el} = 50 \%$, A2030, marginal).

a major additional investment and thereby deteriorate the potential of low CO₂ abatement cost.

The same analysis using a mix grid state signal is conducted as well. The results can be found in figures B.17 to B.20 of the appendix and occur in the same order as the ones elaborated above.

4.3 Effect of the power system

In this section the effects of the surrounding power system on a CG system's performance are analyzed. Comparable to section 4.2 not all considered combinations are elaborated. Instead, exemplary cases are drawn from the set of combinations. These are considered thoroughly. The section is divided into two main parts. First, the NES effects on a BES and its corresponding CG system are presented. This part is followed by an analysis on similar effects for the DS. For both aspects the general performance of CG systems is investigated. Additionally, design implications are identified.

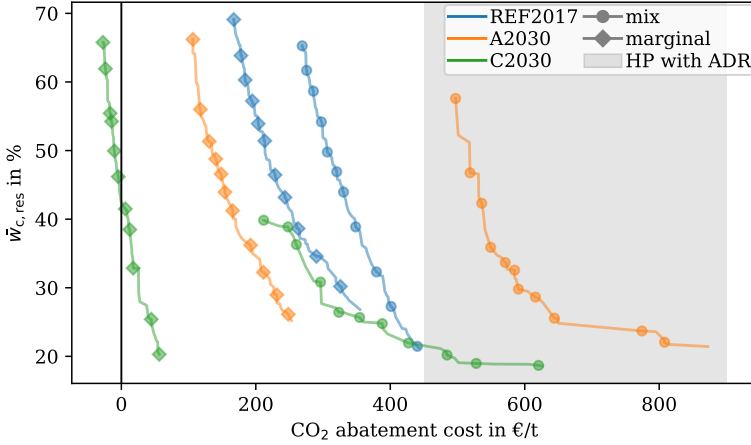


Figure 4.10: Pareto front comparison of marginal and mix signal for different NES scenarios. Assessment against HP system using demand response.

4.3.1 National energy system effect

The NES in which a BES is installed is of major importance. It directly affects its operation and enviroeconomic performance. Three different NES scenarios are considered in this study. Figure 4.10 shows a performance comparison for these scenarios.

The REF2017 scenario offers CO₂ abatement cost that are below the HP with ADR. Further, a slight difference between the marginal and the mixed assessment approach is observed. The exemplary CG system in the A2030 scenario performs differently. First of all, a large gap between the mixed and the marginal approach exists. In this respect, the marginal grid state method shows a clear improvement compared to a REF2017 scenario. Despite, the opposite trend is found for the mixed A2030 case, which shows a performance that is comparable to the reference HP systems. A different effect is observed when switching from the A2030 to the C2030 scenario, that relies even more on the electrification of energy demand and focuses on power generation from PV. Here, a slight improvement is achieved with respect to CO₂ abatement cost and congestion mitigation potential. Additionally, the Pareto fronts of the mixed scenarios tend towards flatter curves in the 2030 scenarios. The congestion mitigation abilities are better using the mixed approach. As a downside, this potential comes at comparably high cost, especially in scenario A2030. Further, it is observed that the potential for congestion management increases from NES scenario REF2017 to C2030.

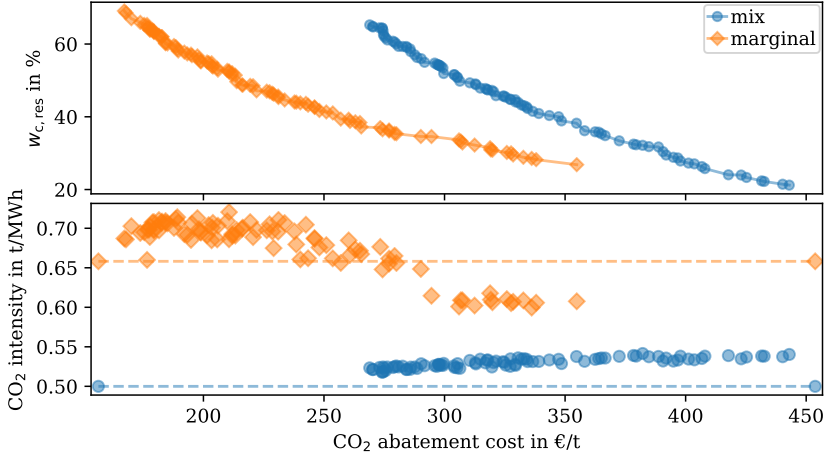


Figure 4.11: Comparison congestion mitigation and NES state exploitation for a mix and marginal evaluation method.

The shape and relative positions of the Pareto fronts can be explained by two main factors. Figure 4.11 addresses the offset that exists between a mixed and a marginal approach. In that sense, the mixed approach shows a significantly lower average CO₂ intensity level, which reduces the environmental values of produced power for the corresponding CG systems. Nevertheless, the comparison also reveals that the CO₂ score is above the annual average for both depicted methods. Only those systems that achieve the best congestion mitigation fall below this average value. The reason are comparably low CO₂ factors that occasionally occur in congestion situations. These are not addressed by systems that are optimized towards low CO₂ abatement cost.

In addition to the grid state signals' influence on the performance, the implications for the CG system design are of interest. To emphasize on that, figure 4.12 shows the design curves for the considered cases. For both, the thermal output of the CG unit and the thermal storage capacity an early increase is observed when applying the mix approach. Beyond that, the TES shows an oversizing for the lowest CO₂ abatement cost already. In comparison to an ordinary TES sizing this corresponds to a factor five increase. This design effect can be explained with low fluctuations in the enviroeconomic value of power. Especially the A2030 scenario shows sparse and infrequent signal peaks that needs to be exploited using a larger CG unit size and TES volume. The large TES dimensions go along with high threshold values for λ_{force} as already presented in section 4.2. These indicate an operational focus on narrow peaks in the enviroeconomic value signal. Additionally, larger forecast horizons are used due to the large

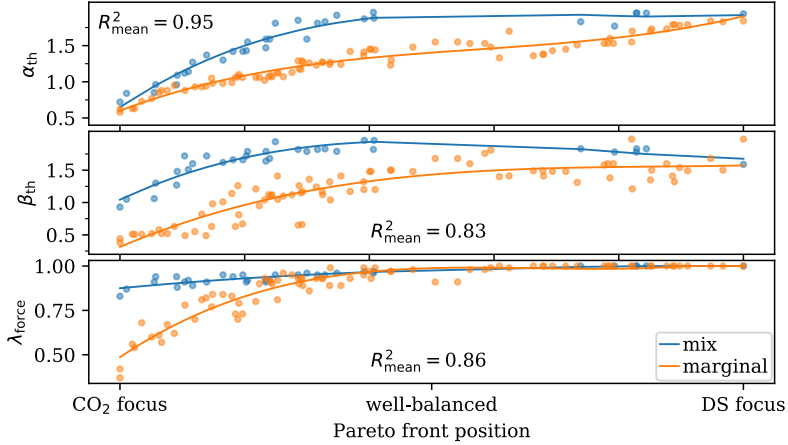


Figure 4.12: Design comparison of mix and marginal approach for a 1'000 m² MFH located in a given surrounding energy system (A2030, $\xi_{el} = 50\%$, $A_{occ} = 40$ m²).

amount of available storage capacity. In contrast, the design following a marginal grid state approach shows a slower increase of the CG system size. Both, α_{th} and β_{th} have a flatter curve over the entire range. Nevertheless, the curves converge to common maximum values that enable relatively high congestion mitigation shares. Due to the lower TES capacity in the beginning of the curves a low starting point for the controller threshold is obtained.

Referring back to 4.10 a second effect on the performance needs to be elaborated. Besides the aforementioned offset which is induced by the grid state approaches, i.e. mix or marginal, the gap between different NES scenarios deserves further attention. Clearly, the performance improves in both aspects from scenario REF2017 to C2030, however the changes in CO₂ abatement cost are more obvious.

Figure 4.13 reveals where these changes originate from. First, the average emission intensities of power decrease over the different scenarios, with the highest values for REF2017 and the lowest for A2030. In spite of that, CG systems in the C2030 scenario achieve a superior performance on that aspect. In fact, both 2030 scenarios are able to keep the average CO₂ intensity clearly above the annual NES average. Compared to that, the REF2017 scenario performs in a bandwidth around the annual average for all obtained CG designs. Additionally, significant differences in the NES average and the power prices achieved by CG are observed. For all investigated NES scenarios the CG systems are able to capitalize on power prices above average. As a matter of fact, CG systems on the lower end of the Pareto fronts obtain the best prices.

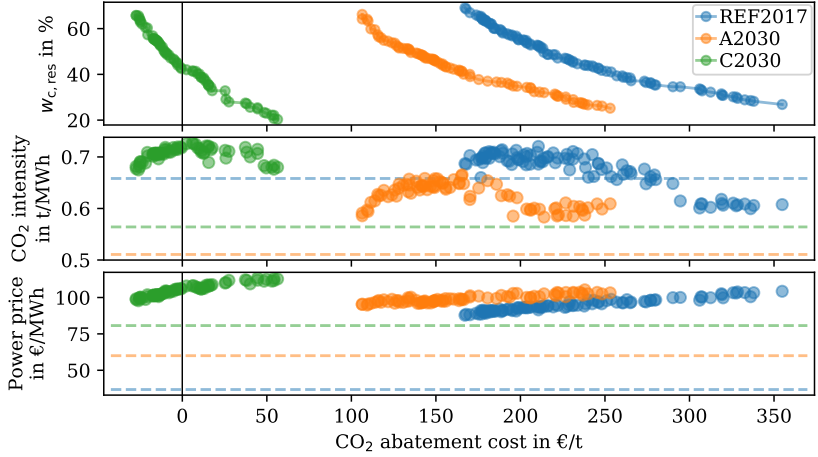


Figure 4.13: Comparison of NES state exploitation for scenarios REF2017 and A2030 using the marginal assessment method.

Just like the grid state signal method, the NES scenario in which a CG system is optimized has an effect on the design. To analyze these effects and to identify general design implications figure 4.14 is used. The first design parameter α_{th} reveals similar values in all NES cases. However, differences are found in the TES sizing where the C2030 scenario shows considerably smaller values in the left part of the curve.

The main reason for this difference lies in the flexibility demand that is characterized by the fluctuation frequency of the NES state. Hence, the NES load and generation structure are of importance in this respect. In comparison to the REF2017 and A2030 scenario the power production within C2030 relies on PV to a greater extend. Additionally, the share of EV in the NES exceeds the A2030 share by the factor ten, which induces intraday fluctuations in the NES residual load. These frequent fluctuations are consequently found in the power plant dispatch and thus in the NES grid state signals. Due to the higher frequency, CG systems in a C2030 scenario necessitate lower temporal flexibility values which keeps the TES size at a low level. The optimized operational design parameter λ_{force} indicates a focus on short-term operation as well.

Considering the former, figure 4.15 shows the potential number of NES-induced forced operations. The C2030 scenario shows considerably higher values compared to other scenarios for similar threshold levels. This fact confirms the higher fluctuations in the NES grid state. In the right end of the design curves that correspond to the lower right part of the Pareto front,

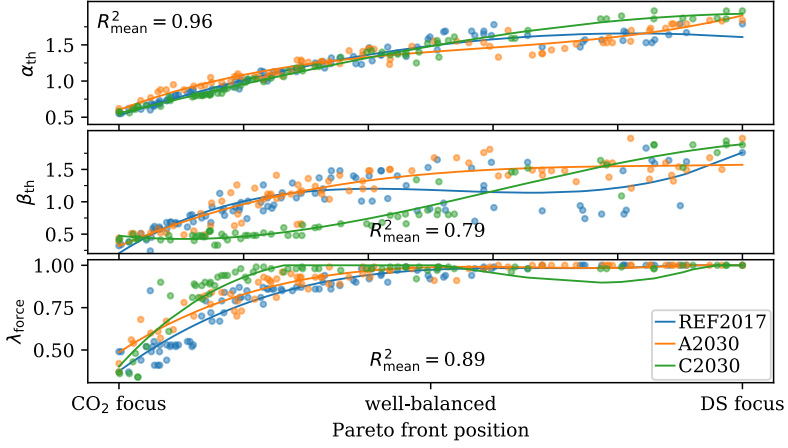


Figure 4.14: Design comparison for different NES scenarios using a 1'000 m² MFH located in a given surrounding energy system ($\xi_{\text{el}} = 50\%$, $A_{\text{occ}} = 40\text{ m}^2$, marginal).

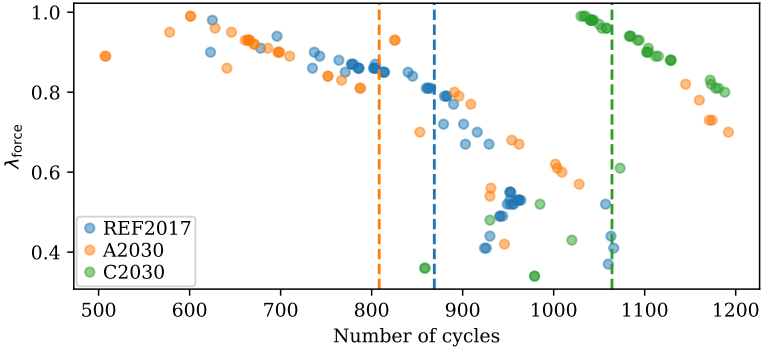


Figure 4.15: Number of NES induced cycles depending on the λ_{force} setting for different scenarios ($\xi_{\text{el}} = 50\%$, MFH 1'000 m² non-retrofit, $A_{\text{occ}} = 40\text{ m}^2$, marginal).

the optimization focus shifts towards improved congestion mitigation. Hence, the obtained results show a need for large CG units and TES.

4.3.2 Distribution system effect

Besides the NES the DS is an essential part of the power system. Especially the level of electrification has an effect on the demand for congestion management and thus also defines the potential for congestion mitigation by CG systems. The performance in terms of Pareto optimality for the analyzed electrification levels are presented in figure 4.16.

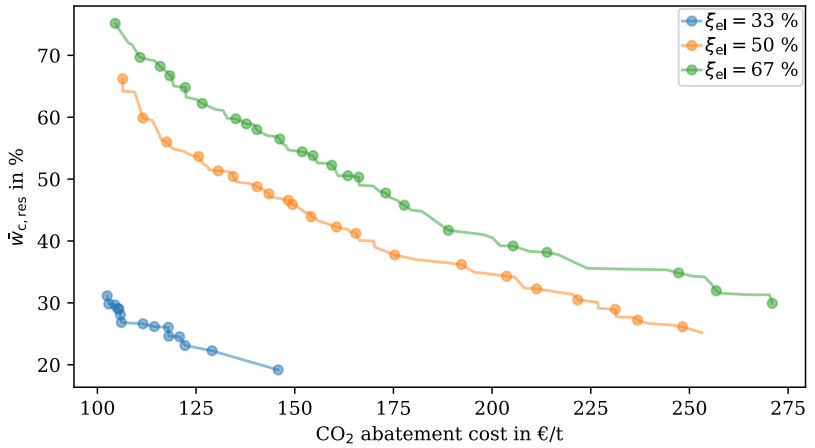


Figure 4.16: Pareto front comparison of different electrification levels in the DS (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, marginal).

Starting with the 33 % electrification case it needs to be pointed out that it has the lowest annual demand for congestion management. This is valid both in terms of congestion power and energy. Hence, already a single CG system in the DS is able to cover a major amount of the demand for congestion energy. In fact, a good grid support performance is achieved even when using the lowest CO₂ abatement cost setup. With larger electrification levels, however, a higher demand for congestion management exists. Accordingly, the share that can be covered by a single CG unit decreases. This is especially true when applying a CG design that offers low CO₂ abatement cost. Nevertheless, when utilizing a more DS oriented design principle congestion mitigation values that are comparable to the 33 % case are achieved. These come at high cost though. The comparison of the three cases shows that the lowest possible CO₂ abatement cost are almost independent of the electrification level.

With respect to the individual density on the Pareto front some conclusions for the suitability of the optimization approach can be drawn. Generally, the infrequent occurrence of congestion situations as in the 33 % case (cf. 2.22) complicates the optimization process. The sparsely populated Pareto front reveals this issue. Especially towards low values of residual congestion energies at the lower end of the Pareto front the evaluation function of the optimization approach is very noisy. This behavior is induced by discrete steps in the congestion mitigation abilities of the simulated CG systems. In the 33 % case only 49 congestion events occur during an entire year. Thus, covering only one additional congestion already affects the congestion management performance significantly. Of course, the same effect applies vice versa.

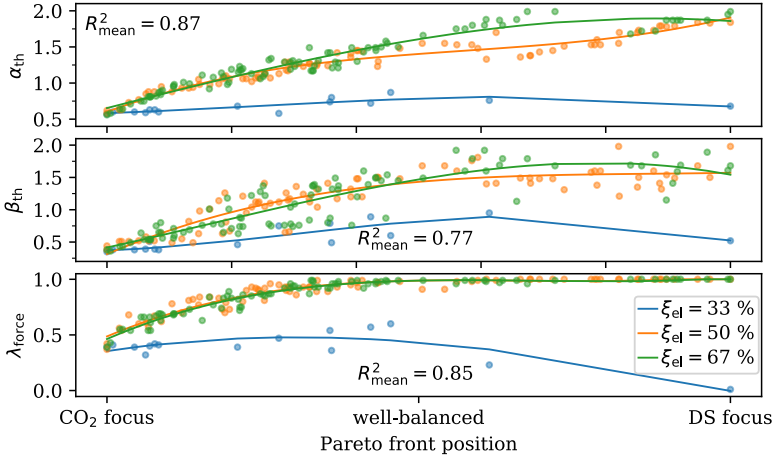


Figure 4.17: Design comparison of different electrification levels (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, marginal).

In order to achieve the aforementioned performance particular design curves are obtained by the optimization. These are depicted in figure 4.17. With respect to the sizing, the medium and high electrification levels show only slight differences. Nevertheless, a trend towards comparably smaller CG units and TES is observed for the 50 % case. This effect can be explained with the lower peak congestion power demand that goes along with a lower share of EV and HP systems in the DS. This observation is especially true for the lowest electrification level of 33 %. In fact, only very little CG system oversizing is needed in this case to achieve a good congestion mitigation performance. Consequently, notable local grid support can be offered at comparably low additional CO₂ abatement cost.

To further analyze the aforementioned design implications figure 4.18 shows the origin of the residual congestion energy. According to the presented shares of the 33 % case, CG systems

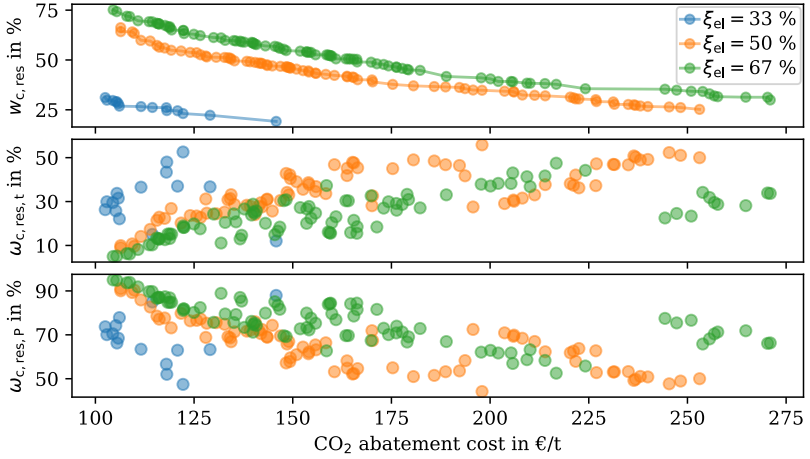


Figure 4.18: Residual congestion shares of different electrification levels (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, marginal).

from the upper left end of the Pareto front miss approximately 20 % of the congestion demand due to temporal reasons. Complementary, 80 % of the congestion energy cannot be mitigated because of a lack of electrical capacity. However, a minor increase of the CG unit and the TES capacity leads to a significant shift according to the design curves. The steep trend of the scatter field confirms this observation. Hence, even shares are found after a 50 % capacity expansion. By contrast, both scatter plots for the higher electrification levels have flatter gradients. Additionally, in these cases CG systems that are optimized towards low abatement cost are hardly able to provide the demanded congestion power. Comparably large additional investments are needed to make up for the deficit.

4.4 Effect of the operation concept

The following two sections present an analysis on different operation concepts that are applied to the CG systems found by the optimization. In that sense, two main questions are addressed. The first section deals with the question of how an optimized grid-driven system performs in comparison to a heat-driven CG system. Further, it is investigated where the differences mainly originate from. The next section analyzes to what extent and in which applications a cooling of excess thermal energy is reasonable.

4.4.1 Operation mode

Within the optimization that is conducted in this thesis a grid-driven operation is applied. The optimization is performed towards low CO₂ abatement cost and improved local grid congestion mitigation. These partially conflicting targets are addressed by the operation concept of the CG systems which is able to react both on the NES and the DS. Therefore, both targets are active in the models applied within the GA. As a result this leads to a Pareto front that shows different optimization target compromises. This section presents the effects that an operational focus on either one of the targets has. For that purpose, the CG systems belonging to the Pareto set are first simulated with a focus on the NES. Afterwards, simulations with a DS focus are conducted. In addition, all Pareto set CG systems that are obtained from the optimization are evaluated using a purely heat-driven operation.

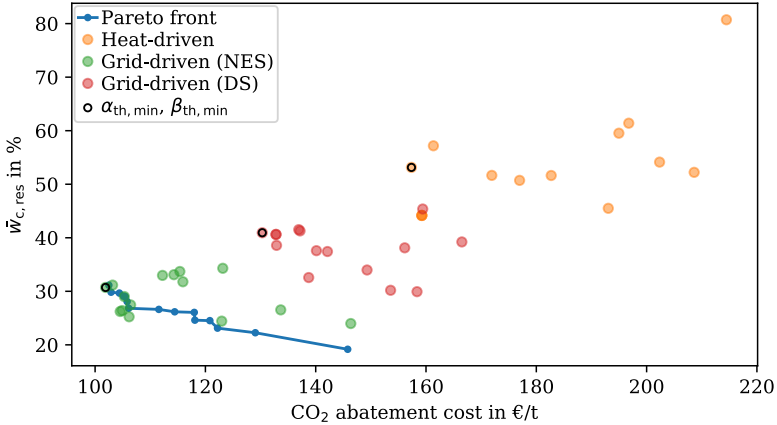


Figure 4.19: Performance comparison of the grid-optimized CG systems with equally sized CG using different operating modes (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, $\xi_{el} = 33$ %, marginal).

Based on these operational variations a comparison of the achieved performance is done. Thus, the main drivers for favorable CO₂ abatement cost or congestion mitigation are identified. Figure 4.19 shows an exemplary result for the A2030 scenario with an electrification level of 33 %. It shows the performance of the Pareto set individuals simulated under different operational schemes. The grid-optimized final Pareto front is the result of the optimization and forms the basis for any further variations. Additionally, a grid-driven case that only utilizes flexibility originating from the NES is depicted. Next to that, the simulation results for a grid-driven operation towards the DS is shown. Finally, the orange scatters indicate

the Pareto set individuals in a purely heat-driven operation mode. The minimum sized CG system is highlighted for each operation mode variation.

The results of the optimization indicate that a better congestion mitigation is usually achieved by larger CG unit sizes accompanied by increased TES volumes. A comparison of the individual scatter fields reveals, that the larger sizing without grid-oriented controls alone achieves no regular improvement with respect to the grid congestion management potential. In fact, larger heat-driven CG systems show rather random performance in that sense. Besides, the CO₂ abatement cost increase with a larger CG system sizing. Among the heat-driven CG systems the best performance in terms of low CO₂ abatement cost is achieved by the minimum sized system that is just able to cover the thermal demand of the corresponding building. The grid-driven systems with focus on the local DS perform slightly better. However, in terms of both abatement cost and congestion mitigation they fall behind the remaining options. The best overall performance is achieved by the grid-optimized individuals. Nevertheless, a grid-driven operation with focus on the NES performs comparably good. Besides, this operation mode seems to be superior over the DS oriented one. This observation once more brings out that a DS-oriented design and operation is complex to achieve when congestion situations have a low frequency of occurrence. In these cases the performance evaluation function is too noisy and stochastic effects dominate. This is especially true when dealing with non-explicit optimization approaches for device scheduling.

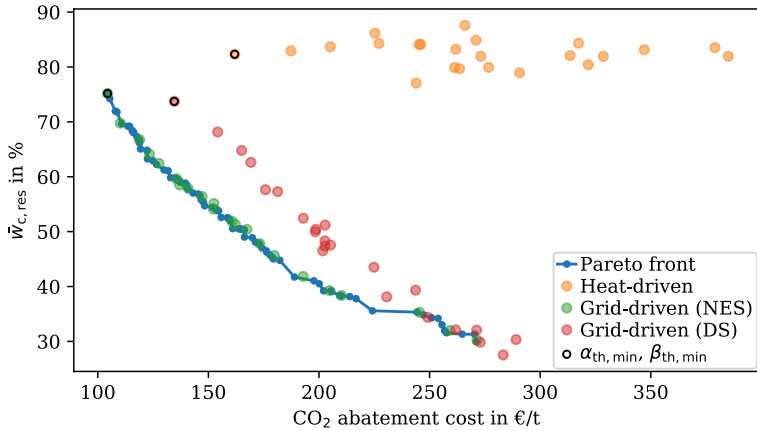


Figure 4.20: Performance comparison of the grid-optimized CG systems with equally sized CG using different operating modes (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, $\xi_{el} = 67$ %, marginal).

In comparison, figure 4.20 shows a slightly different picture. With a higher frequency of occurrence the leverage of stochastic effects in the performance evaluations decreases. Hence, clearer trends are obtained within the scatter fields of the considered CG systems. But still, the heat-driven operation mode is dominated by the others. Besides, it does not benefit from larger CG system sizes in any way. In contrast, the DS-oriented grid-driven operation mode is in parallel to the optimized case over a wide range. In fact, every analyzed individual shows a better congestion mitigation potential compared to the optimized one. This advantage comes at higher cost for CO₂ abatement though, which is indicated by the gap between the two operation modes. The performance using a NES-oriented operation mode is comparable to the optimized one. Only minor differences are recognized, which emphasizes the importance of the NES focus.

4.4.2 Re-cooling option

The operation times of CG systems are often limited by the thermal demand of the corresponding BES. Indeed, the most important criterion is the reliable thermal supply of a building. However, the CG setup that is investigated in this work goes beyond. The grid-driven design and assessment emphasizes the value of the produced power to the surrounding power system. Hence, it might be reasonable to reduce the existing thermal limitations of the BES by dumping excess heat while generating more electrical energy. To assess this option, the CG systems that are found by the optimization are equipped with a RC unit. As demonstrated for the operation mode, the operational focus of the CG system can be switched between pure congestion management and low CO₂ abatement cost. Additionally, both targets can be addressed simultaneously.

An exemplary result for the application of an RC device is presented in figure 4.21 for the scenario A2030 and a DS electrification of 33 %. The optimized Pareto front is similar to the one presented in figure 4.19. In the grid-driven setup CG systems are able to provide flexibility by charging the TES to its maximum temperature. The RC setup additionally enables the dumping of excess thermal energy during these phases to provide a larger amount of temporal and thus energy flexibility. The performance of the RC system that only addresses the flexibility demand of the NES is comparably bad. For all considered systems both the CO₂ abatement cost and congestion mitigation potential is inferior. This result can be explained with two effects. First, the usage of an RC unit requires additional investment that directly affects the CG system's CAPEX. Second, the enviroeconomic value of power needs to be comparably high in phases of RC operation to be favorable. In fact, when dumping the produced heat a CG system is nothing but a small conventional power plant located on the DS level. Thus, it competes with technologies that are found in the merit order such as GOC and GCC. Situations where a CG system is in advantage are very rare and prevent RC-equipped systems to redeem the additional investment for the RC unit.

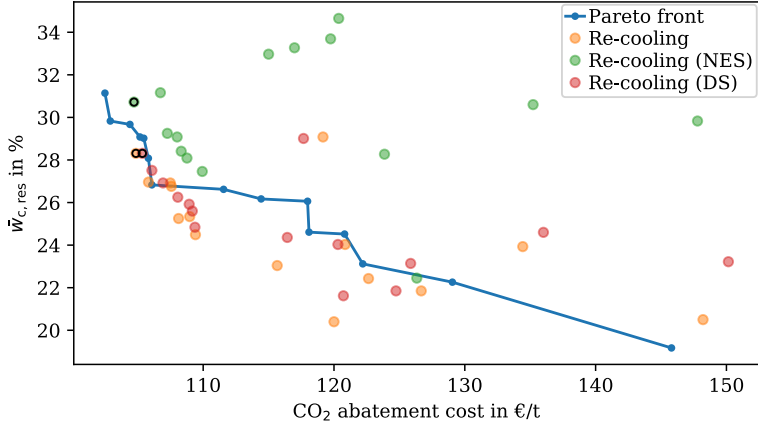


Figure 4.21: Performance comparison of the grid-optimized CG systems with equally sized CG using a RC option (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, $\xi_{el} = 33$ %, marginal).

A better performance is achieved by a DS-oriented RC or when considering both the DS and the NES. These RC cases are comparable to the grid-optimized operation which is represented by the Pareto front. For medium and large CG units and TES volumes many RC systems even achieve favorable results. However, especially the variance of the congestion management potential is high for the presented electrification level of 33 %. Once more, this originates from the low frequency of occurrence for congestion events.

The same CG setup in a DS with 67 % electrification is depicted in figure 4.22 and shows a clearer result. Every considered RC option performs almost similar to the grid-optimized CG system. Nevertheless, the trend that was identified before is confirmed. RC systems with a focus on the NES perform worst in comparison to the other options. The focus on the DS obviously is most significant and is able to further extend the operational flexibility. Especially for larger systems that are found around the lower right end of the Pareto front an additional potential for congestion mitigation is observed. The comparably flat and sparse Pareto front in this area implies strong limitations of the ordinary grid-driven CG. High additional investments are needed to obtain only minor improvements of the congestion mitigation potential. Thus, the operational flexibility provided by RC is comparably valuable.

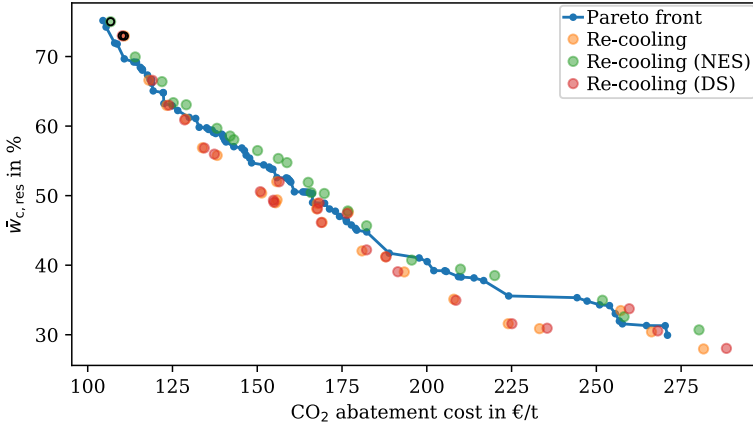


Figure 4.22: Performance comparison of the grid-optimized CG systems with equally sized CG using a RC option (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A_{2030} , $\xi_{el} = 67$ %, marginal).

4.5 Economic assessment

In this thesis the potential of grid-driven CG is analyzed towards low CO₂ abatement cost and congestion mitigation in the local DS. Additionally, the role of distributed CG in the power system and thus power markets is of major interest. A financial evaluation is further needed with respect to the identified congestion management potential since the competitiveness of the application is necessary compared to other options. The following three sections address these topics separately. In contrast to the analyses before each subsection emphasizes on a single aspect only. The first section focuses on pure CO₂ abatement cost where congestion mitigation is out of scope. Second, the LCOE of different CG setups and boundary conditions are determined. Afterwards the detailed view on the congestion mitigation cost in the local DS is given.

4.5.1 CO₂ abatement cost

The analyses in sections 4.1 to 4.4.2 revealed that an increased potential for congestion mitigation is only achieved at comparably high CO₂ abatement cost. Diverse DS are likely to comprise various grid coupled technologies like HP, EV and distributed CG systems. In such systems CG might cover a part of the congestion situations but are not expected to be the only solution. With respect to a suitable CG design the best CO₂ abatement cost are achieved by

small CG systems. Therefore, considering only the CG systems that show the lowest abatement cost appears to be reasonable. In that sense, the results of the best 10 % of each Pareto front obtained by the optimization is depicted in figure 4.23.

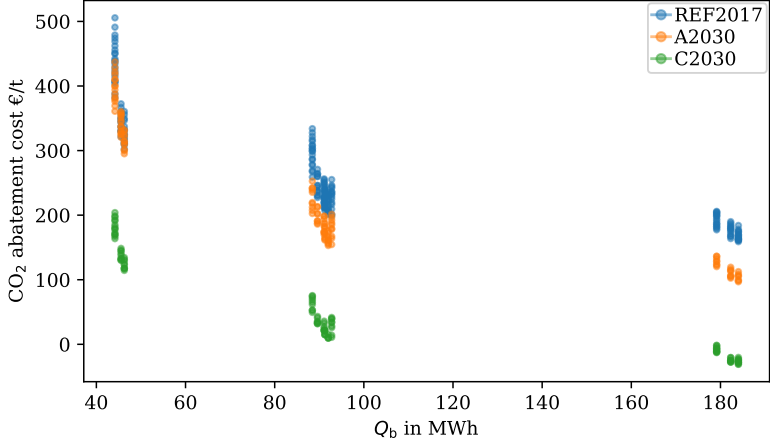


Figure 4.23: CO₂ abatement cost of the best 10 % within the Pareto set plotted against the total heat demand of the investigated buildings.

With the utilization of marginal grid state comparably low CO₂ abatement cost can be achieved. Generally, a positive effect of annual thermal energy demand of a building is observed. The largest building category that is considered in this thesis achieves even negative abatement cost. In addition, a cost-reducing effect is induced by the NES scenario. The improvement from a REF2017 to a C2030 scenario reveals that grid-driven CG systems hold a notable potential to cope with an increasing share of RES in power generation and the electrification of heating and transport. However, within the presented thermal demand clusters difference occur according to the SH to DHW ratio γ_{th} . Buildings with a lower γ_{th} values generally show higher CO₂ abatement cost and a larger variance. These become evident especially in the REF2017 scenario and preferably in buildings with a low heat demand.

The results using a mixed grid state method can be found in figure B.26 of the appendix. However, the achievable CO₂ abatement cost differ drastically under consideration of this method. A notable share of CG systems do not save CO₂ emissions in comparison to a reference GB system. The residual setups show a large variance in performance. Generally, a higher heat demand leads to CO₂ reductions at favorable cost. However, these are not even closely competitive compared to the results obtained using a marginal method.

4.5.2 Levelized cost of electricity

The LCOE are an important measure to economically assess a power generation technology with respect to its competitiveness in the power market. Since the CG system setup that is considered in this thesis is meant to be an integral part of the power system the LCOE method is applied as well. The exemplary result of a 1'000 m² non-retrofit building with an occupant density of 40 m² is presented in figure 4.24. For this case a design that is optimized for a marginal grid state approach is used. It shows the LCOE of all considered individuals over the Pareto front position. Using this relative measure enables the comparison of different NES scenarios in a clearly arranged way.

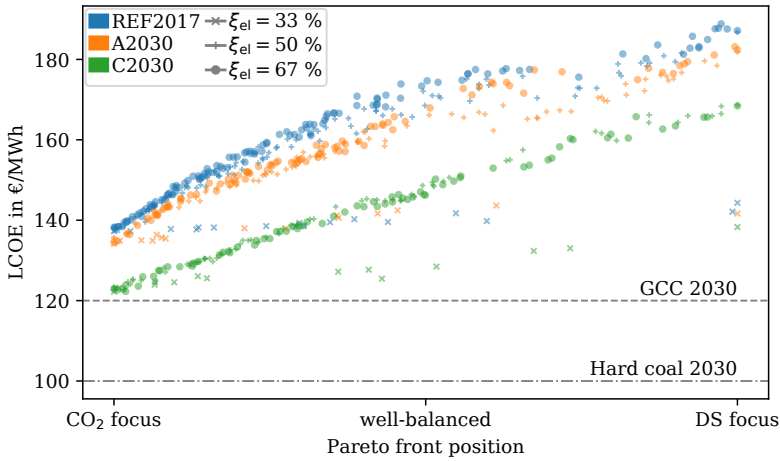


Figure 4.24: LCOE of a CG system for different NES scenarios and DS electrification levels (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², marginal). Conventional LCOE according to Buttler and Spliethoff (2016).

The scatter fields show that the considered NES scenario generally plays a crucial role. According to this, the LCOE in a REF2017 are the highest with a minimum value of 138 €/MWh. With an increasing congestion mitigation potential and thereby larger CG system size the LCOE rise up to 185 €/MWh. Slightly below the values of the A2030 scenario are found. The minimum value that is observed at the CO₂ focused end of the Pareto front is comparable to the REF2017 scenario. However, the curve shows a lower gradient. In comparison, the C2030 shows considerably lower LCOE with a minimum of 121 €/MWh for the best CG system. Additionally, the variance in this case is lower.

The level of electrification obviously has an effect on the LCOE as well. Although the difference between $\xi_{el} = 50$ % and $\xi_{el} = 67$ % is almost negligible, a clear effect for the lowest

electrification level is observed. The corresponding CG systems show lower LCOE with a slow incline of the curve over the relative Pareto front position. This is due to the moderate increase in CG unit in TES size for these systems which is presented in figure 4.17 as well.

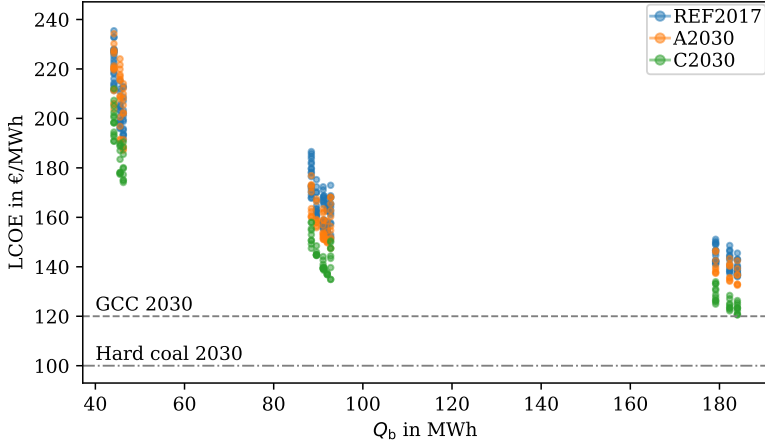


Figure 4.25: LCOE of the best 10 % within the Pareto set over the total heat demand of the investigated buildings.

As for the absolute CO₂ abatement cost a small CG system sizing is favorable when it comes to financial considerations like LCOE. Therefore, the most competitive systems are generally found at the upper left end of the Pareto front. An overview of different CG systems depending on the absolute thermal demand of a building is depicted in figure 4.25. It reveals that the annual thermal energy demand of a building is the most important factor to achieve low LCOE. The building floor area has no specific relevance which is emphasized by the results shown. Between 80 and 100 MWh of annual heat demand all 500 m² non-retrofit and 1'000 m² retrofit buildings are found. Both achieve similar LCOE.

4.5.3 Congestion mitigation cost

Besides low CO₂ abatement cost the mitigation of local grid congestion is a further target of the considered grid-driven CG systems. Since two partially conflicting optimization targets exist a clear cost accounting to either one of the goals is not possible. In this sense the initial investment into a CG system is able to reduce the CO₂ emissions and provide a reliable power supply to the NES. The same CG system, however, also offers a degree of congestion management potential. Nevertheless, considering the results presented leads to a reasonable

measure to assess the cost for congestion mitigation. Based on the results found so far CG systems that ensure lowest possible CO₂ abatement cost are favorable if alternative measures to tackle grid congestion exist. Alternative options are additional buildings equipped with a grid-driven CG unit or DSM technologies, e.g. battery storages or grid-driven HP. In that sense, the oversizing of a particular CG unit and the corresponding additional investment is solely accounted for the purpose of congestion management. Thus, the marginal congestion mitigation cost per kWh are obtained.

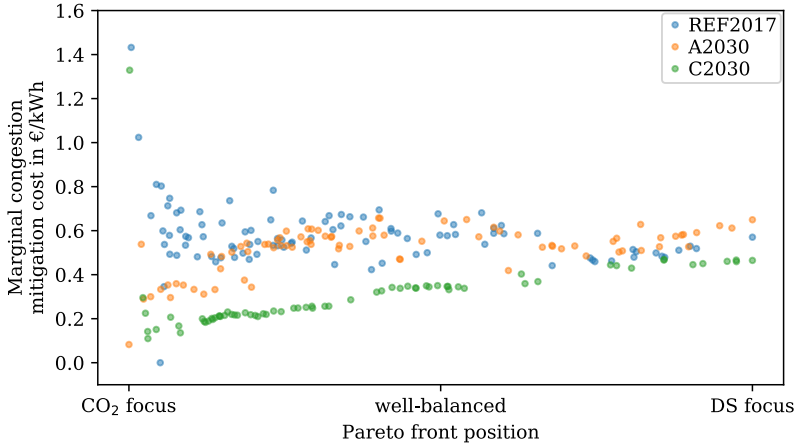


Figure 4.26: Marginal cost of congestion mitigation for different NES scenarios ($\xi_{el} = 50$ %, MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², marginal).

Figure 4.26 shows the results for a medium electrification level of the DS. First, a general dependency of the marginal congestion mitigation cost towards the NES scenario exists. Both 2030 scenarios achieve low congestion mitigation cost in the left part of the Pareto front. With increasing abatement cost, induced by larger CG system sizes, the mitigation cost increase as well. The reason is that added capacity only achieves a decreasing benefit for the mitigation of congestion. Hence, the marginal cost increase which is especially true for the A2030 scenario. For the REF2017 scenario a different trend is observed. A comparably strong increase of TES volumes at the upper left end of the Pareto front leads to high additional investments in order to improve the congestion management potential. After this early increase, however, the storage capacity stays at a moderate level. Further congestion management improvements are mainly achieved by increasing the thermal output of the CG unit. This change in capacity is efficiently exploited and thus leads to constant marginal congestion management cost in the further course. Towards larger sized CG systems with DS focus the marginal congestion mit-

igation cost converge to a value of approximately 0.5 €/kWh. Additional results for different electrification levels can be found in figure B.27 to B.28 of the appendix.

5 Discussion

Energy systems currently develop towards a higher share of power generation from RES. Most likely, this development will be accompanied by the electrification of transport and heat supply. In such an environment CG could be an important element by evolving from pure local supply of heat and power to a fully dispatchable, grid-integrated asset. Thus, CG could support the reliable operation of the local and national electricity system. Additionally, CO₂ savings in comparison to the separate generation of heat and power at comparably low cost might be achieved. This thesis presents a new design and assessment methodology that is applied to a set of different building setups in various energetic scenarios.

5.1 Applied methodology

Within the presented study physical models with a rule-based control approach are applied. These controls are compatible with market available technology. Further, the detailed modeling approach considers important effects such as return temperatures from the heat emission system. Additionally, the stratification within a TES that strongly influences the system's flexibility is included. Thus, the optimization obtains realistic results that are used to draw clear conclusions. However, the aforementioned methods necessitates heuristic optimization which is found to be a GA in this work. Although GA and physical models constitute a powerful combination they also bring some challenges.

First, the computational effort is high since the evaluation function of the GA needs to be computed very often. Second, only non-explicit optimization can be conducted using this approach. Hence, the optimization cannot guarantee a global optimum. It runs the risk to converge towards a local optimum only. Due to the stochastic nature of a GA multiple repetitions of the algorithm need to be conducted to obtain reliable results that are sufficiently close to the true Pareto front. Furthermore, the optimal control of the CG system following a grid state signal is not possible. In turn, this lack leads to a noisy target objective function. However, this is mainly an issue for low electrification levels due to very few and infrequent congestion situations. In addition to that, the forecast horizon which was expected to have notable influence on the performance of the CG system has only a limited and rather undefined effect on the CG performance.

With respect to that, the formulation of a MILP could be an alternative to overcome the above issues partially. However, drastically simplified models would be necessary in this case

which is critical in terms of grid flexibility calculation. Especially simplifications of TES models need to be considered thoroughly. Nevertheless, a MILP formulation that uses a non-physical model for the TES could be a reasonable alternative that is able to ensure the optimal control of a CG system. Such an approach, however, would need to go beyond an ideally mixed water storage tank. Consequently, the computational burden would rise again. Another alternative approach is the combination of a MILP-based MPC with a reduced order physical model of the CG system as used in this work. A test revealed that the computational burden increases by a factor of 50 compared to the application of a rule-based control scheme.

Despite the aforementioned challenges the application of GA is found to be most suitable and revealed valuable results that provide a good foundation for the presented design analysis. Clear trends and implications with respect to a suitable design of a grid-driven CG system are identified. Additionally, various effects of the power system structure and the building application onto the CG system performance in terms of CO₂ abatement cost and congestion mitigation potential are identified.

5.2 Obtained results

The analysis investigates 216 combinations where each is optimized towards the minimization of CO₂ abatement cost and congestion management in the local DS. From multiple candidate design parameters of a grid-driven CG system four essential ones are identified. With the CG unit capacity and the TES volume two of the identified parameters directly address the equipment sizing. The remaining design parameters refer to the controls of the CG system and its optimal settings.

With respect to the building application, the optimization results generally reveal that the thermal demand has a significant influence on the CG system's performance. However, the heat demand and its structure is thereby influenced twofold. First, it is affected by the building envelope and second, the building's occupants are of major importance. Regarding the building envelope a large effect of building's retrofit state and floor area is observed that consequently influences the CG system's performance. Specifically, the optimization results show that larger buildings with a higher annual heat demand are clearly in favor over smaller ones. This is true both in terms of CO₂ abatement cost and congestion mitigation potential. In contrast to HP systems, non-retrofit buildings and grid-driven CG systems constitute a good fit due to the high flow temperatures that are needed in a radiator-based heat emission system. HP systems are better combined with low temperature floor heating systems. The comparison with a study by Patteeuw et al. (2015) reveals that CO₂ abatement below those of a HP system using ADR can be achieved, if suitable boundary conditions apply. Some considered setups are even able to achieve negative CO₂ abatement cost.

Further, the optimization results show that the thermal demand structure has an effect too. It is expressed with the ratio of SH to DHW demand γ_{th} and can be influenced either by changing the SH or the DHW demand. The building envelope affects the former, where buildings with a lower insulation standard and thereby higher γ_{th} values perform better. In such cases the thermal demand is mostly determined by SH which results in a smooth demand curve. As a consequence, moderate fluctuations and less distinctive peak loads reduce the need for relative TES capacity. Another aspect originates from the power system where the demand for flexibility, both terms of NES and DS, mostly occurs during the heating season. Compared to summer the average enviroeconomic value of power is high during that phase. This aspect is especially true for power system scenarios that consider electric HP as the main HVAC technology. Accordingly, these high values are naturally exploited by the CG systems due to a continuous SH demand.

This study considers the building size in terms of different floor areas. Generally, smaller buildings perform worse which on the one hand originates from their lower thermal demand. On the other hand the simulation results reveal another effect. Smaller buildings have fewer occupants which leads to a higher simultaneity factor and thereby larger minimum system size. Thus, a negative effect on the CO₂ abatement cost is observed. Along with that, the congestion mitigation potential is positively influenced. Additionally, small retrofit buildings show a strong performance sensitivity towards changes in γ_{th} . The described effects are found for the mixed grid state method as well.

A demand for SH exists only in winter and during the transition phases. In contrast, a heat demand for the preparation of DHW is found around the entire year. This reliable demand was expected to hold a certain potential for flexible CG operation. The expectation is not proven by the optimization results though. Instead, no positive effect from stretching the operation of CG units into the summer is observed. Hence, higher occupant densities with the corresponding DHW demand cannot gain any advantage. In fact, low occupant densities have a positive influence since less occupants per m² reduce the internal gains. Consequently, the thermal demand that needs to be supplied by the CG system increases. This effect overcompensates the lack of DHW demand and leads to more operation hours during winter where the enviroeconomic value of power is high and congestion situations are more likely. Additionally, the thermal demand is less dominated by DHW supply and therefore it shows smaller peaks which reduces the need for thermal storage capacity. For the same reason additional TES volume is needed in cases of high occupant density which leads to higher CAPEX. If congestion management is primarily concerned then high density buildings are in advantage. These generally bring along larger TES volumes and CG units that perform better in terms of congestion management. The improved congestion mitigation comes at comparably high additional CO₂ abatement cost though.

The analysis of the NES effects on the CG performance shows that especially the choice of the grid state method can have an extraordinary effect. The degree mainly depends on the considered NES scenario and ranges from a low effect in a REF2017 scenario to a huge one in the C2030 one. Generally, the application of a mixed signal leads to larger CG systems. Especially with growing RES shares the fluctuation of the enviroeconomic value of power becomes lower with limited peaks. In turn, larger TES volumes and CG units are necessary to exploit those phases which results in higher investments and therefore increased CO₂ abatement cost.

In contrast, the CO₂ abatement cost are reduced from 2017 to 2030 when using the marginal method. Specifically the C2030 scenario brings favorable conditions for CO₂ reductions by grid-driven CG systems. High average prices and CO₂ intensities can be exploited with comparably small TES volumes. The main driver for this effect is the higher fluctuation frequency of the enviroeconomic value of power in the C2030 scenario. The higher maintenance cost for cycling of the CG plant that come along with the fluctuations in the NES are overcompensated.

Fluctuations, however, might be lower in the actual NES of 2030 in comparison to the simplified NES model presented in this work. It considers the German power system as a separate one, although it is part of the integrated European transmission system (ENTSO-E) in reality. Due to simplifications within the model, power imports and exports to neighboring countries are not considered. As a consequence, the amount of RES curtailment is overestimated by the model. Hence, the lowest prices and emission intensities are expected to be higher in a real 2030 scenario. Vice versa, the highest prices and emission intensities might be different as well. Additionally, a lower frequency of occurrence of such peak values is expected. The actual amount, however, will again depend on the NES structure of the neighboring countries in the ENTSO-E system. Nevertheless, lower spreads and less fluctuations in the enviroeconomic value of power are likely which is unfavorable for the utilization of flexibility options on the NES level.

With higher shares of RES and cleaner conventional power generation technologies like GCC, the boundary conditions for CG will become unfavorable in terms of CO₂ abatement. On the contrary, very high prices might occur in times with low RES generation. The capability to reduce CO₂ emissions will shrink, but the importance to have backup capacity in the NES will grow. Yet, the effect for CG systems is unclear at this point and depends on the technologies that will accompany the increasing share of RES.

When considering the LV part of the power systems, several effects are observed based on the optimization results. The level of electrification clearly determines the congestion management demand and thereby the maximum potential that can be addressed by CG systems. With respect to the minimum achievable CO₂ abatement cost only a very limited effect is seen. Starting from a 33 % case a strong effect on the optimal CG system design is observed. Only

at this electrification level the demand for congestion management is very infrequent and makes an optimization towards DS support unreasonable.

In general, frequency and peak values of DS congestions are found to have a strong leverage on CG unit's potential to support the grid. These characteristics depend on several factors. In addition to the technology adaptation, i.e. HP and EV share, the assumed operation concept of those technologies is of importance. In this study DSM for both technologies is out of scope. In addition to that, electrification levels above 50 % in a DS are expected to be rare and probably do not represent the common situation in a LV grid for the next decade. Nevertheless, high electrification levels might constitute a reasonable projection towards 2050. As addressed before, a technical potential grid-driven CG in terms of congestion management exists. However, mitigating those congestions comes at increased cost mainly driven by CAPEX. The accounting for congestion-induced capacity expansion gives an insight on the cost that congestion mitigation by grid-driven CG has. In that sense, reasonable marginal congestion mitigation cost are only obtained in DS with frequent congestion situations.

The grid-driven CG system that is considered in this work uses an electric HR. This concept allows to spare a peak load GB. Compared to an ordinary sized CG unit the power generation is notably increased at a minor additional investment. The simulation results reveal that this novel concept is able to reliably supply the building's heat demand.

With respect to the dimensioning, minimum sized CG systems always achieve the lowest CO₂ abatement cost. This implies that the value of additional operational flexibility is limited in the considered scenarios. An oversizing for CO₂ abatement reasons would occur if a larger spread in the enviroeconomic value of power was observed. Since it is determined by the product of CO₂ intensity and power price, both quantities need to oscillate in phase to provide a signal that is exploitable. However, this is rarely the case in today's merit order that mostly offers CO₂ intensive power generation at lowest prices. However, this aspect experiences a change. Especially a price increase of CO₂ emission allowances is able to swap positions within the merit order. As a result, CO₂ intensive technologies such as hard coal will show higher marginal cost of electricity. This effect improves the competitiveness of flexible CG in comparison to conventional generation and might also lead to larger CG system sizes.

Alternatively, a higher electrical efficiency of the CG unit would have the same effect. In that sense, the application of fuel cell is promising if cycling and modulation capabilities of this technology evolves. Besides, larger MFH with a floor area clearly above 1'000 m² would provide further reductions in CO₂ abatement cost. These, however, are often coupled to the MV grid and would therefore not be able to serve the LV network. As already mentioned before the congestion management performance is mostly determined by the CG unit's power output. The storage size plays only minor role, since congested grid situations mostly occur for some hours only. These time frames can often be addressed without the need for additional TES volume.

Further, the presented work shows that the operational concept is crucial for the performance of CG systems. Heat-driven systems cannot compete at all with grid-driven ones. In these setups the theoretical potential for low CO₂ abatement cost and congestion mitigation stemming from additional capacity is not transferred to actual performance. If the mitigation of frequent congestions is most important grid-driven concepts with focus on the DS achieve slightly better results. The focus on the DS leads to additional CO₂ abatement cost though.

Single grid-driven CG systems are generally not capable of entirely eliminating congestions in the LV network. In practical applications multiple CG systems need to be deployed where each one of them supplies a share of the necessary congestion power. For that reason, a design focus on CO₂ abatement cost seems more favorable. Anyway, a comparison of CG systems that focus on the NES with those that consider both the NES and DS identified the NES-orientation to be most important. In the considered scenarios the CG operation invoked by the NES often overlaps with local grid congestions.

An RC device to supplement grid-driven CG is investigated in this work as well. The results show that RC is mostly needed in summer when the enviroeconomic value of power is usually low. Hence, a very limited benefit is obtained to lower the CO₂ abatement cost. Further, only few grid congestions occur outside of the heating season, since these are usually induced by HP and EV. Instead, grid congestions mostly occur in winter when the thermal demand is high anyway. Here RC is not needed in most cases. To some extent, however, excess heat is dumped during the transition phases. Nevertheless, CO₂ abatement cost are not positively affected. An operational focus on NES is not reasonable since the reduction of CO₂ abatement cost by RC requires high enviroeconomic value of power. Regarding the local DS, a minor additional reduction of congestions is possible for larger CG systems when the DS is considered. Generally, the achieved benefit from RC is very limited. The actual improvements do not justify the added complexity of the system and its operation.

Another important research question that is addressed in this work is the role that grid-driven CG might take in the power market. In this respect, the LCOE of CG in comparison to conventional generation assets are determined. Results show that large CG systems achieve LCOE of around 120 €/MWh in the 2030 scenarios. Thus, the obtained LCOE are in the range of conventional medium load power plants which are less flexible. Generally, the trend towards increasing CO₂ prices constitutes an advantage for the LCOE of CG systems as well. Beyond 2030 CG might even be cheaper than gas and hard coal power plants without heat extraction due to their decreasing capacity utilization. But still, conventional capacity is needed, especially during summer since RC is not an economically feasible option so far. Nevertheless, positive effects might come from new CG technologies, such as fuel cells, that achieve higher electric efficiencies in comparison to combustion engines.

6 Conclusion and outlook

6.1 Conclusion

In this work a novel design approach for grid-driven CG systems was presented. A power system oriented assessment method was applied to determine the CO₂ abatement cost and congestion management potential of CG in a reference LV network. The analyses find, that the choice of the NES state signal is crucial for the CO₂ abatement cost of a given CG system. Using a marginal assessment method leads to favorable results over a mixed NES state. Future scenarios of the year 2030 further increase the advantage of the marginal method. In addition, the application of a marginal assessment is found to better account for the mechanisms within the NES that are determined by its merit order. Consequently, a clear incentive for the provision of operational flexibility by CG systems is offered.

Buildings with a high thermal energy demand were identified to be the favorable application for grid-driven CG. In terms of CO₂ abatement cost they are able to compete with HP systems. Even negative CO₂ abatement cost were obtained in a 2030 scenario comprising a large share of PV and EV. The design analysis reveals that a CG system sizing that exceeds the thermal demand of the building is generally not suitable. Regarding CO₂ abatement cost, the best performance is achieved by minimum sized monovalent systems. Only if the congestion mitigation potential is of prime importance, larger CG units and TES sizes are applicable. Minimum sized systems additionally benefit from frequent fluctuations of the NES state. In these scenarios the utilization of operational flexibility is comparably high. Nonetheless, the congestions in the considered LV reference network cannot be mitigated completely by a single BES. Additionally, congestion management by single CG systems comes at high additional cost. Therefore, clusters of suitable buildings need to be equipped with grid-driven CG. Depending on the cluster size and the availability of alternative congestion management options, a CG system should primarily be sized with regard to low CO₂ abatement cost.

The performance of a CG system in terms of CO₂ abatement cost and congestion mitigation largely depend on the operation mode. Using a grid-driven operation is clearly in favor over a heat-driven concept. Specifically the integration of the NES state into the control strategy is crucial to obtain good results. Thus, design approaches for CG systems must consider unit sizing and controller settings in combination. Within the investigated scenarios the introduction of a RC unit to dump excess heat was not able to reduce the CO₂ abatement cost. Nevertheless, for CG systems with a design focus on DS service further improvements of the congestion mitigation potential are achieved. For the assessment of grid-driven CG as a

reliable and flexible generation technology the LCOE were calculated. The results show that the best performing CG systems are able to compete with flexible GCC and hard coal power plants in the 2030 scenarios. Increasing prices for CO₂ allowance certificates and higher shares of intermittent RES in power generation towards 2050 are expected to further improve the competitive position of grid-driven CG systems. Especially the installation of PV generation capacities is able to enforce this trend.

6.2 Outlook

The methodology applied in this work was proven to be viable. Using a GA algorithm in combination with BPS ensures a high level of detail. Nevertheless, the results reveal that in case of infrequent flexibility demand a rule-based control approach might not be sufficient. Thus, the presented approach could be extended by an MPC that explicitly optimizes CG unit's operational schedule.

Further, the design optimization was conducted for the year of installation only. Since CG systems have an expected service life of 20 years a design approach could be extended by means of life cycle assessment. Thus, changing boundary conditions would be considered. However, the uncertainty on the design assumptions would remain. A deeper insight on the robustness of the design optimization would be achieved using uncertainty analysis. Nevertheless, tackling the aforementioned research questions increases the computational effort even further.

An application of the presented design method in larger, not necessarily residential, buildings that are connected to the MV network could be valuable. Since fewer congestion situations on the MV level are expected, an optimization towards low CO₂ abatement cost seems more promising. Large grid-driven CG systems that supply district heating networks might obtain beneficial performance in terms of CO₂ abatement cost and further reduce the LCOE. CG systems using fuel cells hold substantial energetic potential. Due to high electrical efficiencies fuel cells could lead to different conclusions, especially with respect to the application of RC devices. However, the general economic competitiveness of this technology has not been proven yet. Besides CG, the presented design and assessment methodology can be applied to other grid-coupled HVAC technologies. Especially reversible HP systems that use heat and cold storage tanks hold the potential to provide operational flexibility during the entire year. Nevertheless, an optimal design is a prerequisite.

The power system models that are used in this work are simplified. First, the consideration of the entire ENTSO-E grid could affect the grid state signal of the NES. The sensitivity of the optimization results towards these changes could be investigated. Second, congestion power could be supplied by other options than CG. Thus, leaving out these technologies might overestimate the actual demand for congestion management. Therefore, an approach

that combines reactive power supply, grid-driven CG systems and DSM of HP and EV might reduce the actual congestion mitigation potential.

Finally, the analyzed CG systems should be implemented in real BES. Along with this, the proposed marginal emission assessment and the marketing of produced power need to be integrated in the regulatory framework. In addition, the determination of a time-variant CO₂ intensity needs to be coordinated with the transmission system operators and transmitted to individual BES.

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Appendix

A Scenario input data

Table A.1: Building stock in Germany with heat demand, share of building category and retrofit share (Deutsche Energie-Agentur GmbH, 2018)(Ziesing, 2018)

Scenario	Q_{SH} [TWh/a]	Q_{DHW} [TWh/a]	$\gamma_{Q,MFH}$	$\gamma_{Q,SFH}$	γ_{retro}
REF2017	427	94	0.38	0.62	0.2
A2030	386	94	0.38	0.62	0.5
C2030	386	94	0.38	0.62	0.5

Table A.2: Technology shares for electrification of heating and transport sector (Deutsche Energie-Agentur GmbH, 2017)

Scenario	Building type	γ_{CG}	γ_{HP}	γ_{EV}
REF2017	SFH	0.0034	0.039	0.0012
	MFH	0.01	0.0166	
A2030	SFH	0.026	0.164	0.0215
	MFH	0.049	0.067	
C2030	SFH	0.01	0.35	0.215
	MFH	0.005	0.247	

Table A.3: Overview of installed generation capacity in different NES scenarios

Technology	Scenario		
	REF2017	A2030	C2030
	RES [GW]		
PV	42.4	72.9	104.5
Wind onshore	50.5	74.3	85.5
Wind offshore	5.4	20.0	17.0
Biomass	7.6	6.0	6.0
Run of river	5.6	5.6	5.6
	Conventional [GW]		
Nuclear	9.5	0.0	0.0
Lignite	21.2	9.4	9.4
Hard coal	25.0	13.5	8.1
GCC	12.9	16.1	16.7
GOC	16.7	16.7	16.7
Misc	8.7	7.4	7.0
	Storage power [GW]		
Pumped hydro	9.5	11.6	11.6
Battery	0.4	2.7	12.5
	Storage capacity [GWh]		
Pumped hydro	39	39	39
Battery	0.9	3.6	16.4

B Optimization results

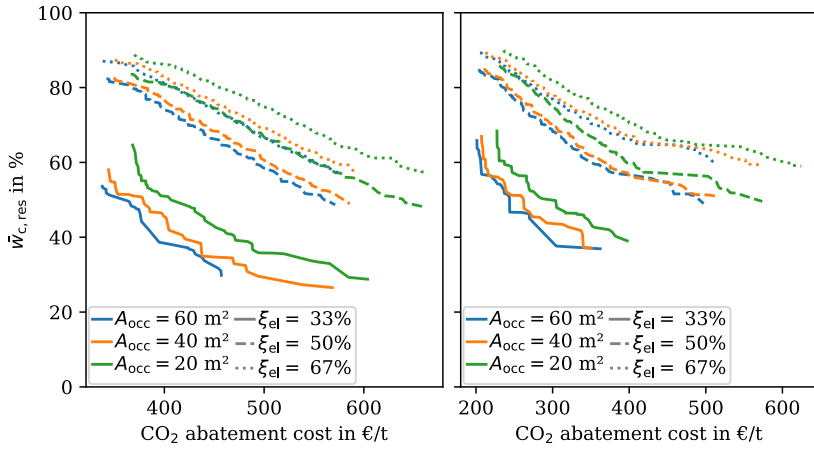


Figure B.1: Pareto fronts of non-retrofit MFH with 500 m² floor area in scenario REF2017.
Mixed (left) and marginal (right)

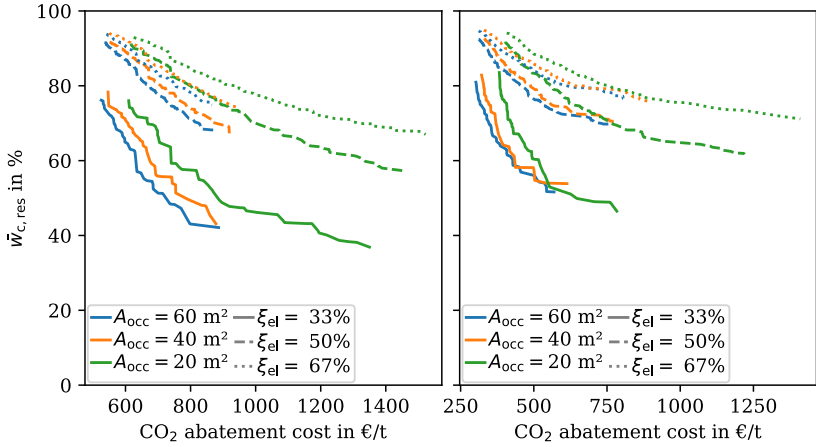


Figure B.2: Pareto fronts of retrofit MFH with 500 m² floor area in scenario REF2017. Mixed (left) and marginal (right)

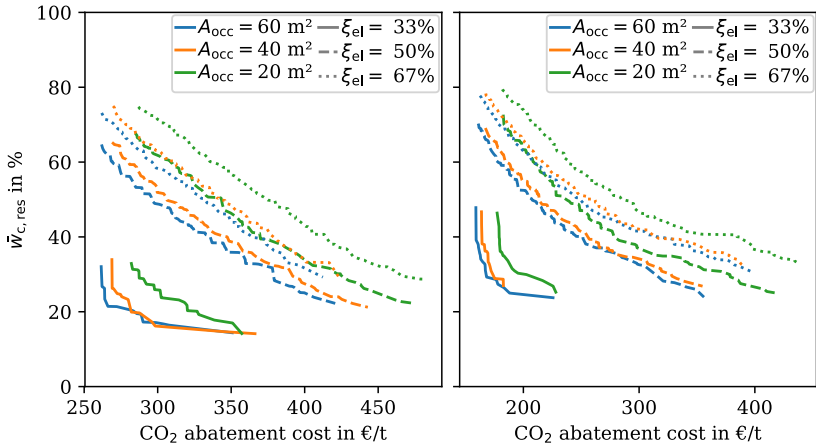


Figure B.3: Pareto fronts of non-retrofit MFH with 1'000 m² floor area in scenario REF2017. Mixed (left) and marginal (right)

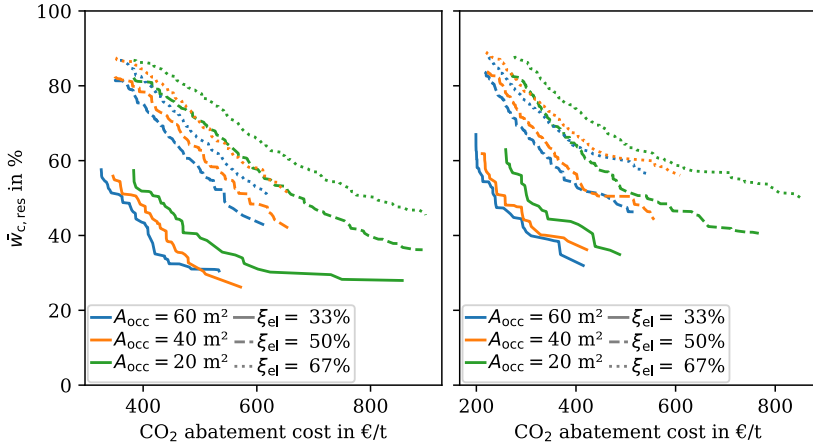


Figure B.4: Pareto fronts of retrofit MFH with 1'000 m² floor area in scenario REF2017. Mixed (left) and marginal (right)

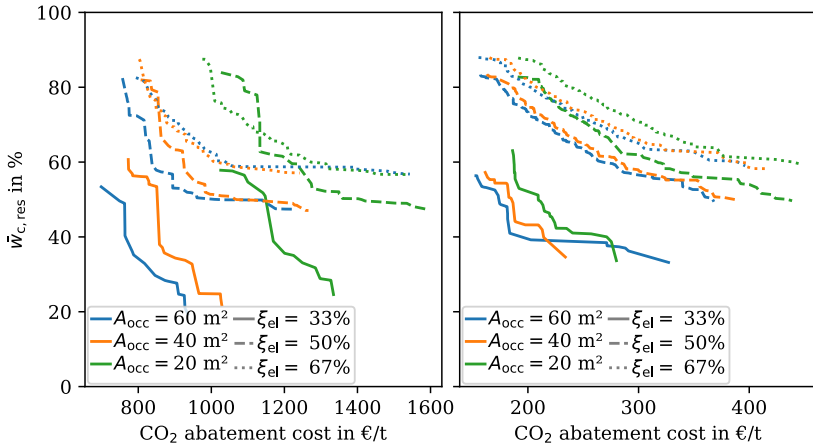


Figure B.5: Pareto fronts of non-retrofit MFH with 500 m² floor area in scenario A2030. Mixed (left) and marginal (right)

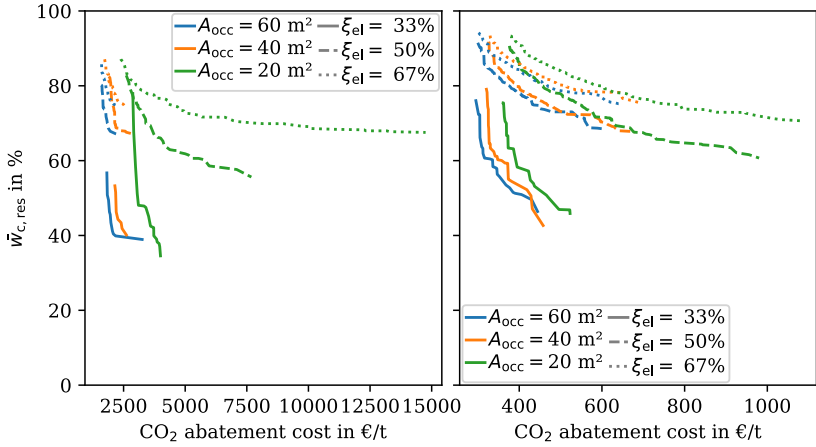


Figure B.6: Pareto fronts of retrofit MFH with 500 m² floor area in scenario A2030.
Mixed (left) and marginal (right)

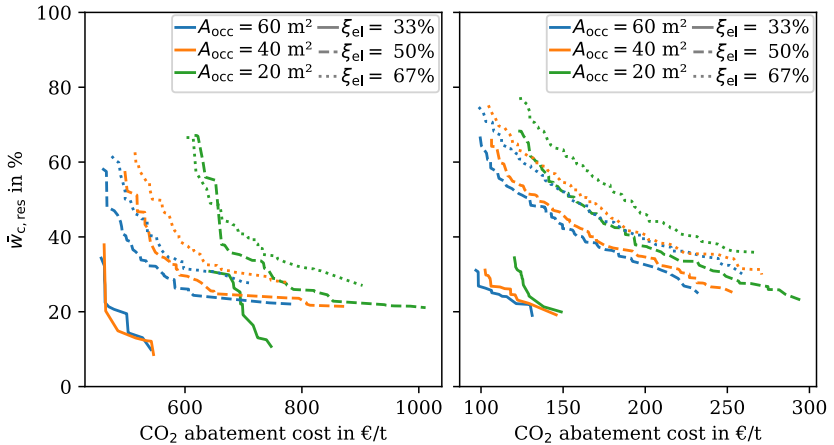


Figure B.7: Pareto fronts of non-retrofit MFH with 1'000 m² floor area in scenario A2030.
Mixed (left) and marginal (right)

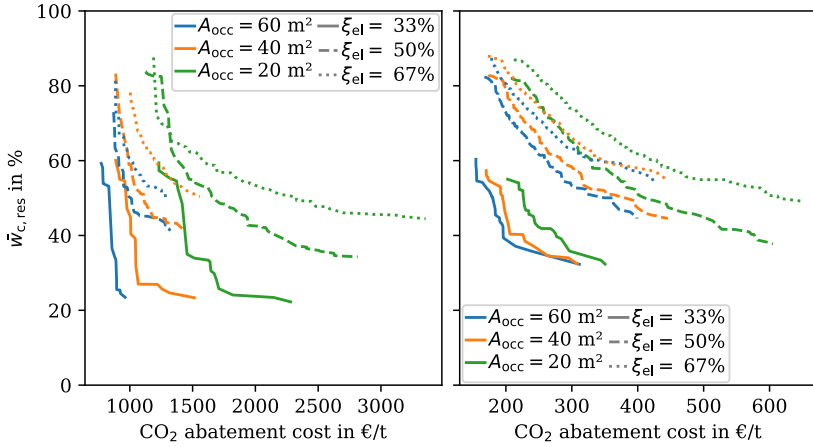


Figure B.8: Pareto fronts of retrofit MFH with 1'000 m² floor area in scenario A2030. Mixed (left) and marginal (right)

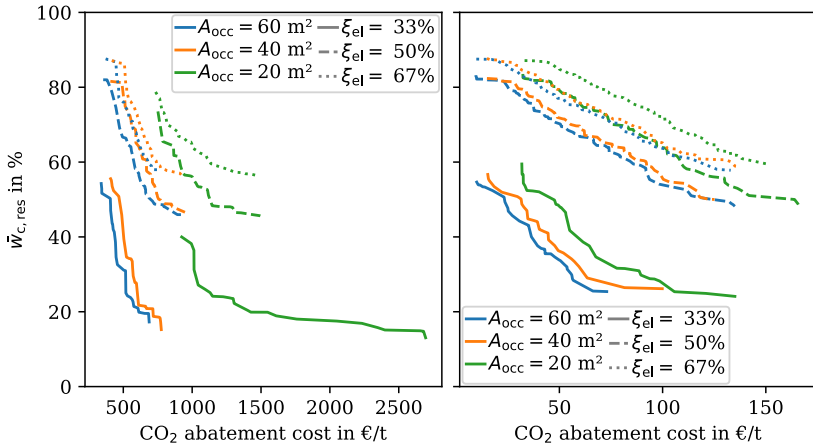


Figure B.9: Pareto fronts of non-retrofit MFH with 500 m² floor area in scenario C2030. Mixed (left) and marginal (right)

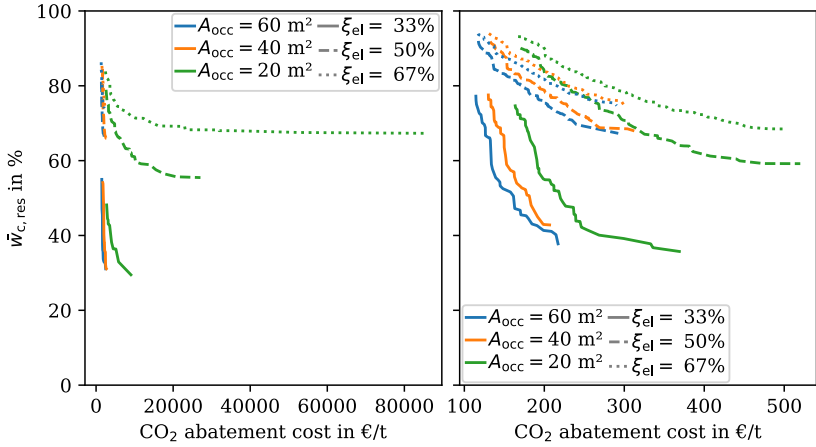


Figure B.10: Pareto fronts of retrofit MFH with 500 m² floor area in scenario C2030. Mixed (left) and marginal (right)

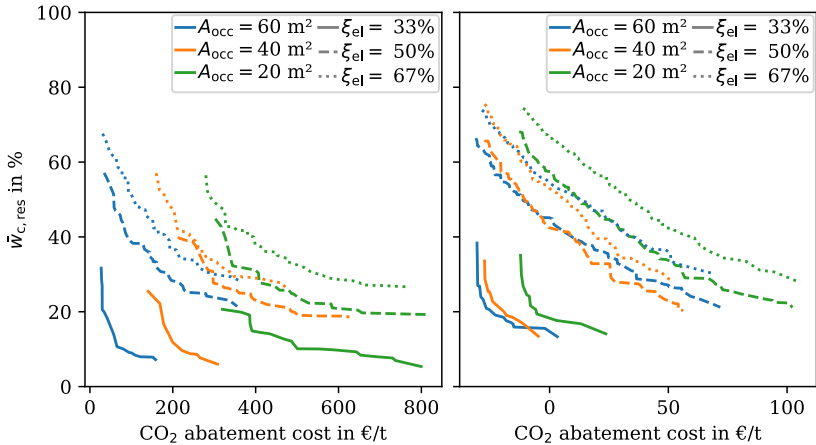


Figure B.11: Pareto fronts of non-retrofit MFH with 1'000 m² floor area in scenario C2030. Mixed (left) and marginal (right)

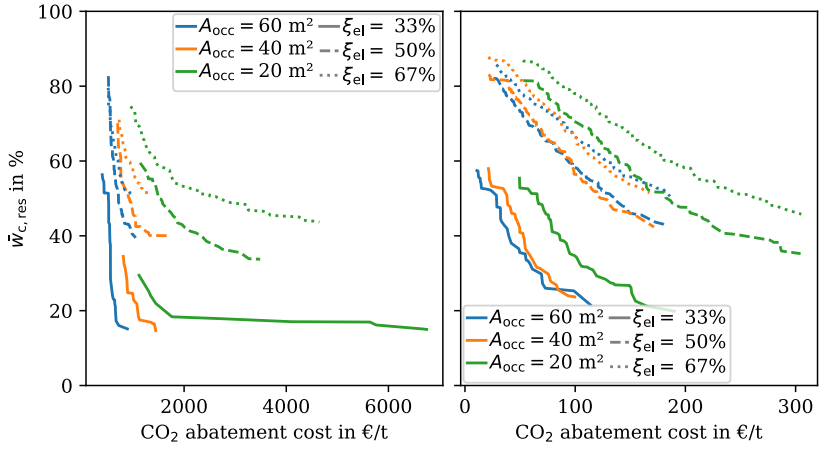


Figure B.12: Pareto fronts of retrofit MFH with 1'000 m² floor area in scenario C2030.
Mixed (left) and marginal (right)

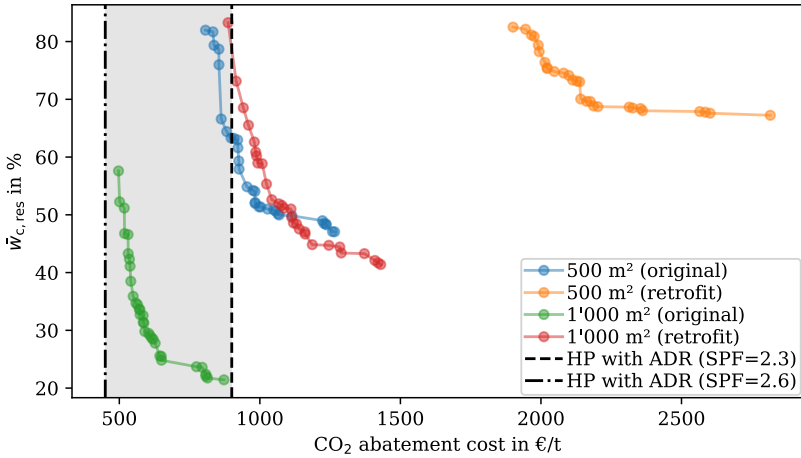


Figure B.13: Performance comparison of different BES ($\xi_{el} = 50\%$, A2030, mix).

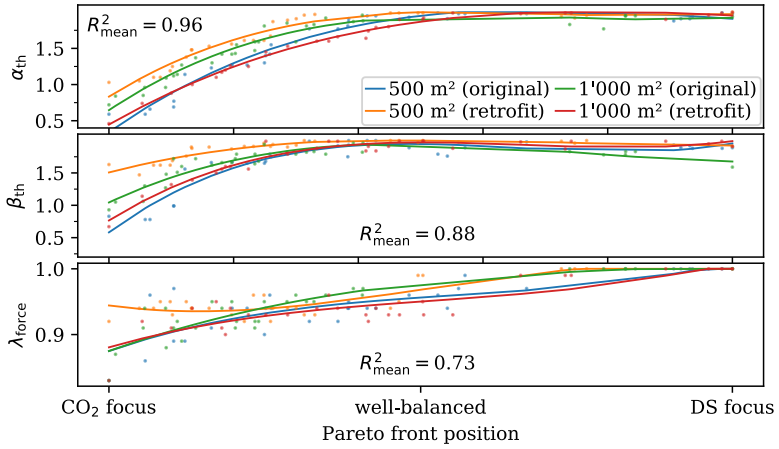


Figure B.14: Design comparison of different BES ($\xi_{el} = 50\%$, A2030, mix).

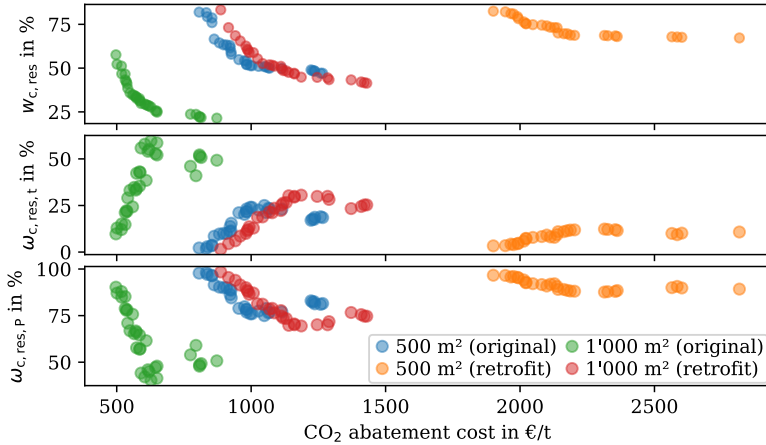


Figure B.15: Residual congestion shares for different BES ($\xi_{el} = 50\%$, A2030, mix).

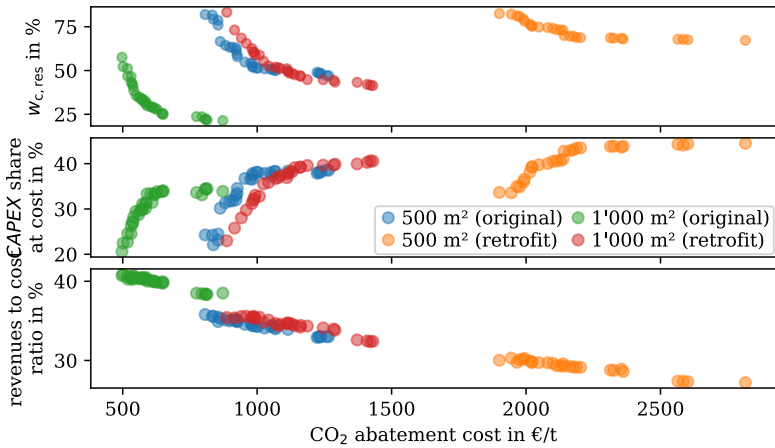


Figure B.16: Cash flow structure of different BES ($\xi_{el} = 50$ %, A2030, mix).

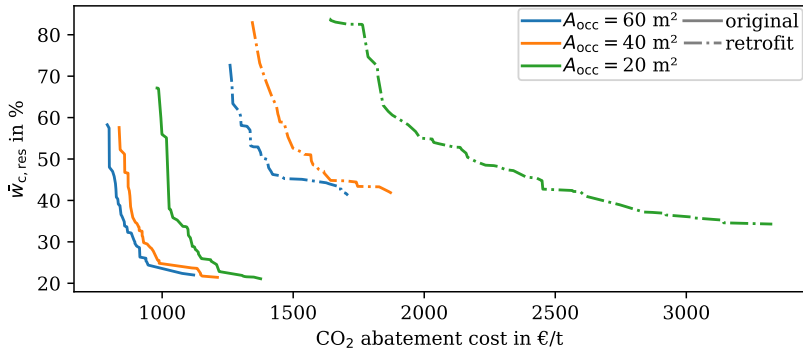


Figure B.17: Performance comparison of different occupant densities in a 1'000 m² MFH ($\xi_{el} = 50$ %, A2030, mix)

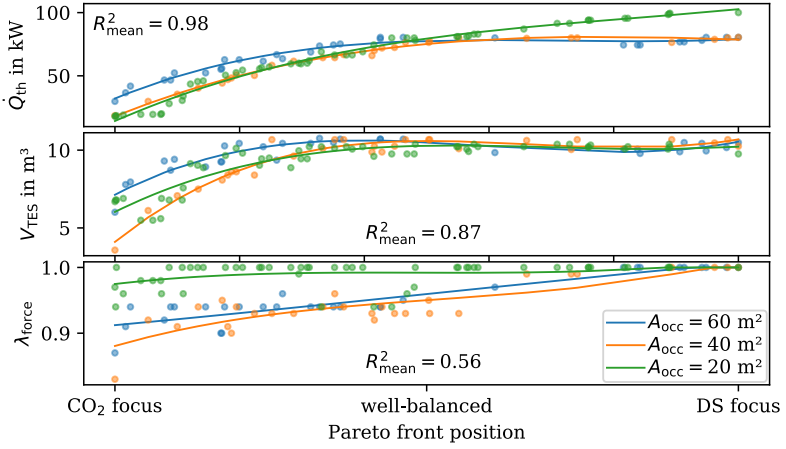


Figure B.18: Design comparison for different occupant densities ($\xi_{el} = 50\%$, A2030, mix).

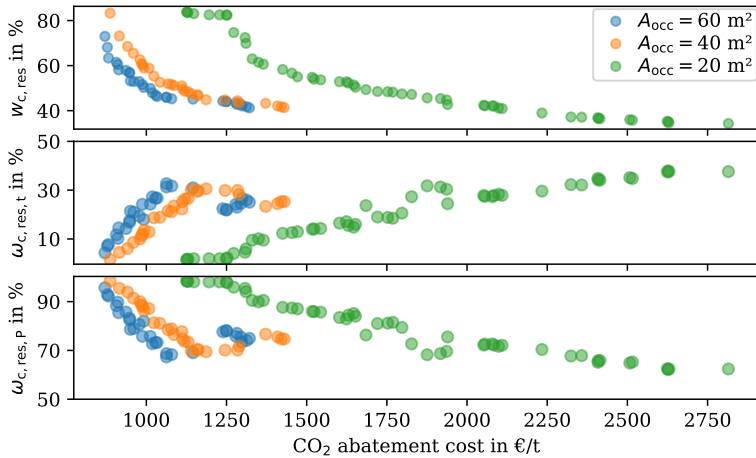


Figure B.19: Residual congestion shares for different occupant densities ($\xi_{el} = 50\%$, A2030, mix).

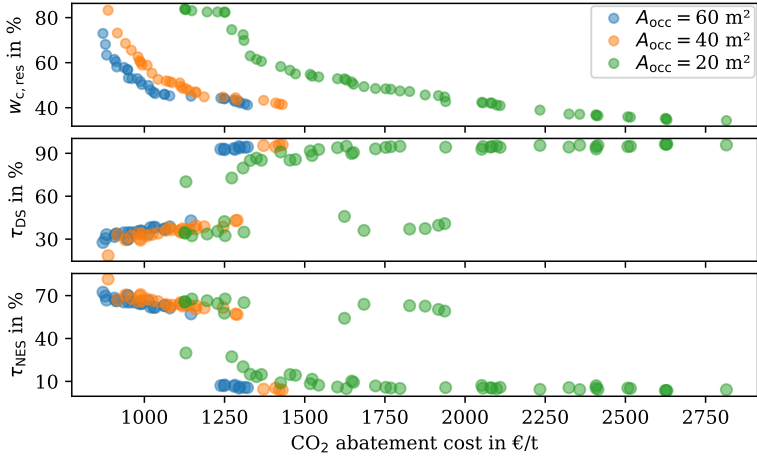


Figure B.20: Operational focus of different occupant densities ($\xi_{el} = 50 \%$, A2030, mix).

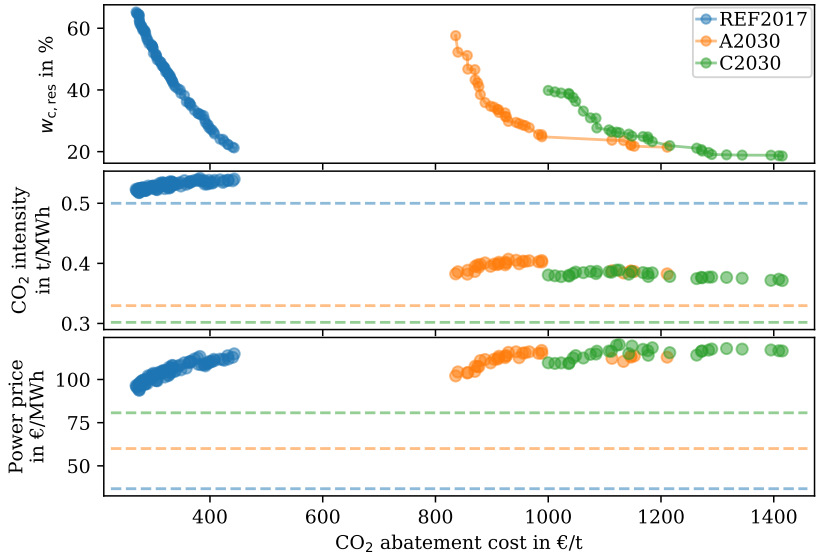


Figure B.21: Comparison of NES state utilization for scenarios REF2017 and A2030 using the mixed assessment method.

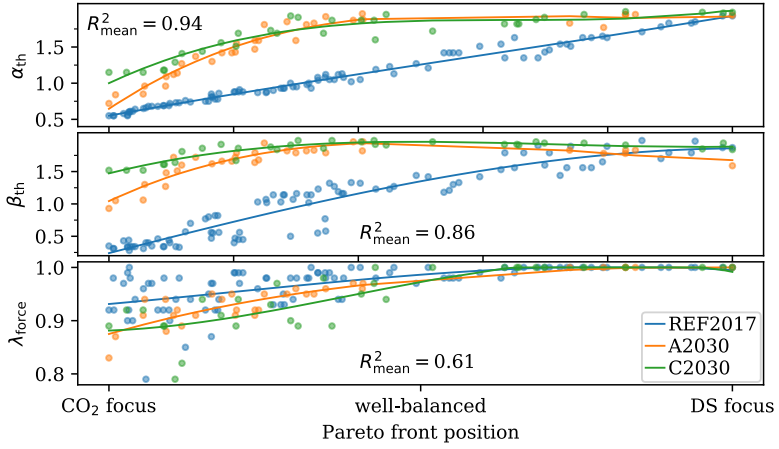


Figure B.22: Design comparison for grid state signals ($\xi_{el} = 50$ %, $A_{occ} = 40$ m², mix).

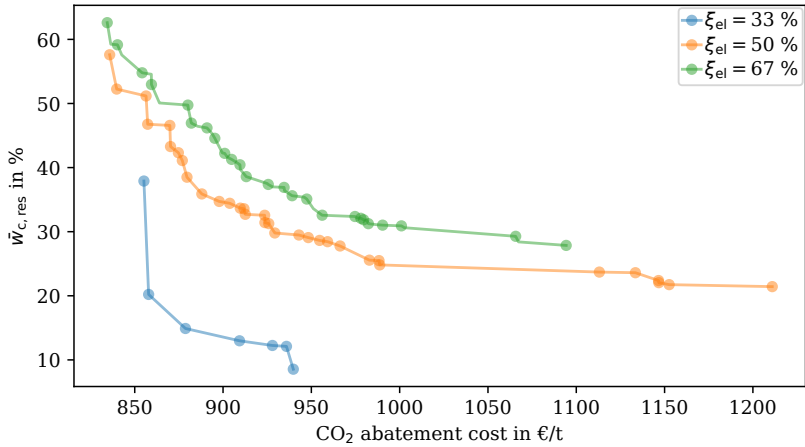


Figure B.23: Pareto front comparison of different electrification levels (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, mix).

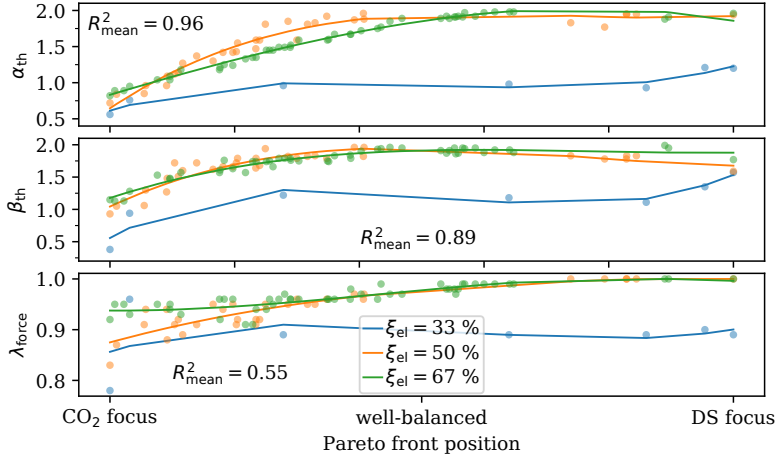


Figure B.24: Design comparison of different electrification levels (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, mix).

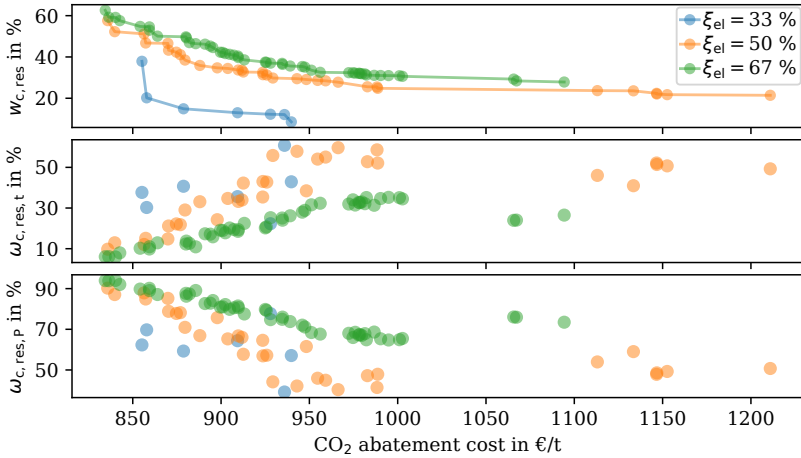


Figure B.25: Residual congestion shares of different electrification levels (MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², A2030, mix).

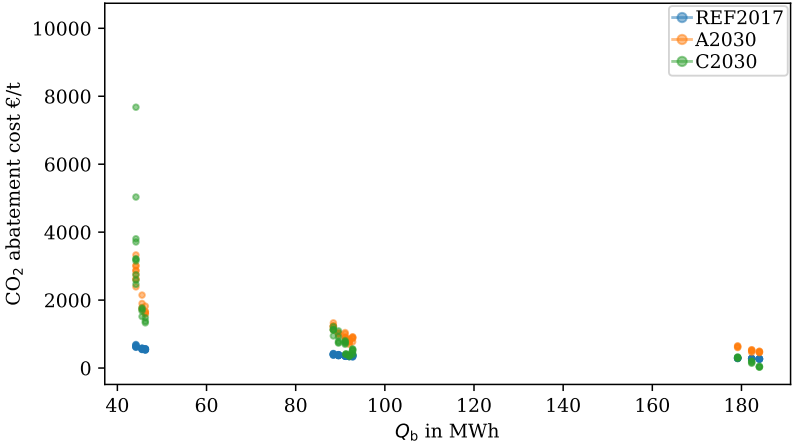


Figure B.26: CO₂ abatement cost of the best 10 % within the Pareto set plotted against the total heat demand of the investigated buildings (mix).

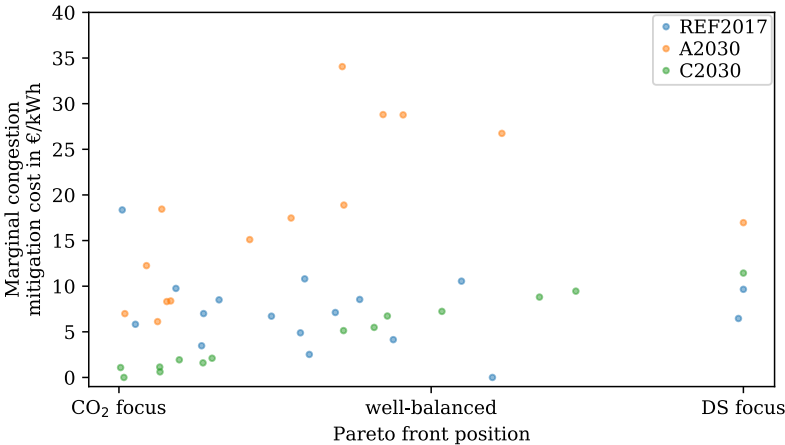


Figure B.27: Marginal cost of congestion mitigation for different NES scenarios ($\xi_{el} = 33\%$, MFH 1'000 m² non-retrofit, $A_{occ} = 40$ m², marginal)

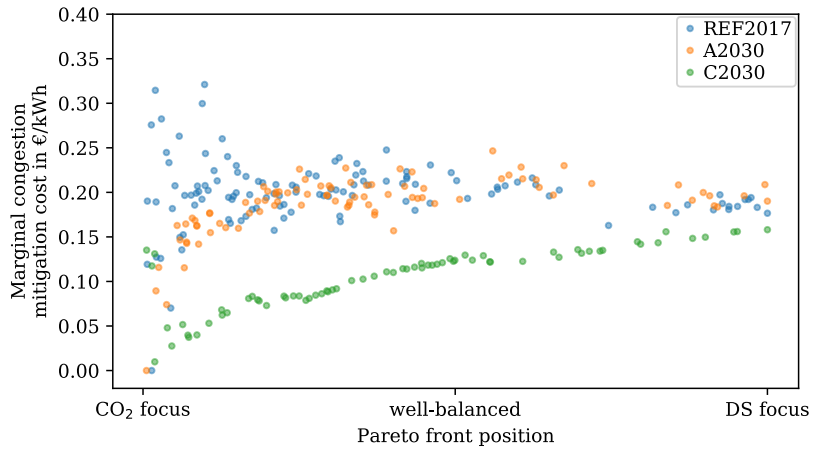


Figure B.28: Marginal cost of congestion mitigation for different NES scenarios ($\xi_{\text{el}} = 67\%$, MFH 1'000 m² non-retrofit, $A_{\text{occ}} = 40$ m², marginal)

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The increasing deployment of renewable energy sources will lead to larger fluctuations in electricity supply. Additionally, the electrification of transport and thermal energy supply of buildings will impose new loads to the electric distribution grids. These developments will occasionally lead to grid overload caused by heat pumps and electric vehicles. Besides, a significant heat demand caused by buildings needs to be efficiently supplied. Cogeneration units could be utilized as flexible, distributed power plants that offer reliable and fully controllable supply while mitigating load induced grid congestions in the electric distribution system. For that purpose, time resolved states of the electric energy system need to be determined and transmitted to the cogenerators to enable grid balancing. A dynamic CO₂ factor of the national power plant portfolio and the demand for congestion power in the grid are considered. Thereby, dynamic operation and control strategies are implemented and the design of cogeneration units is optimized. The performance assessment is conducted based on CO₂ abatement cost and the potential for grid congestion management. As a result, the optimal design of cogenerators is found and the influence of different factors like building application, power system context and control approach on the design and performance of the cogeneration system is analyzed. General design implications are identified. An economic evaluation indicates the role of cogeneration in a future power system.

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