Decision Making under Uncertainty and Competition for Sustainable Energy Technologies

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Statement of Originality

I, Lajos Maurovich Horvat, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

This dissertation addresses the main challenges faced in the transition to a more sustainable energy sector by applying modelling tools that could design more effective managerial responses and provide policy insights. To mitigate the impact of climate change, the electric power industry needs to reduce markedly its emissions of greenhouse gases. As energy consumption is set to increase in the foreseeable future, this can be achieved only through costly investments in more efficient conventional generation or in renewable energy resources. While more energy-efficient technologies are commercially available, the deregulation of most electricity industries implies that investment decisions need to be taken by private investors with government involvement limited to setting policy measures or designing market rules. Thus, it is desirable to understand how investment and operational decisions are to be made by decentralised entities that face uncertainty and competition.

One of the most efficient thermal power technologies is cogeneration, or combined heat and power (CHP), which can recover heat that otherwise would be discarded from conventional generation. Cogeneration is particularly efficient when the recovered heat can be used in the vicinity of the combustion engine. Although governments are supporting on-site CHP generation through feed-in tariffs and favourable grid access, the adoption of small-scale electricity generation has been hindered by uncertain electricity and gas prices. While deterministic and real options studies have revealed distributed generation to be both economical and effective at reducing CO_2 emissions, these analyses have not addressed the aspect of risk management. In order to overcome the barriers of financial uncertainties to investment, it is imperative to address the decision-making problems of a risk-averse energy consumer. Towards that end, we develop a multi-stage, stochastic mean-risk optimisation model for the long-term and medium-term risk management problems of a large consumer. We first show that installing a CHP unit not only results in both lower CO_2 emissions and expected running cost but also leads to lower risk exposure. In essence, by investing in a CHP unit, a large consumer obtains the option to use on-site generation whenever the electricity price peaks, thereby reducing significantly its financial risk over the investment period. To provide further insights into risk management strategies with on-site generation, we examine also the medium-term operational problem of a large consumer. In this model, we include all available contracts from electricity and gas futures markets, and analyse their interactions with on-site generation. We conclude that by swapping the volatile electricity spot price for the less volatile gas spot price, on-site generation with CHP can lead to lower risk exposure even in the medium term, and it alters a risk-averse consumer's demand for futures contracts.

While extensive subsidies have triggered investments in renewable generation, these

installations need to be accompanied by transmission expansion. The reason for this is that solar and wind energy output is intermittent, and attractive solar and wind sites are often located far away from demand centres. Thus, to integrate renewable generation into the grid system and to maintain a reliable and secure electricity supply, a vastly improved transmission network is crucial. Finding the optimal transmission line investments for a given network is already a very complex task since these decisions need to take into account future demand and generation configurations, too, which now depend on private investors. To address these concerns, our third study models the problem of wind energy investment and transmission expansion jointly through a stochastic bi-level programming model under different market designs for transmission line investment. This enables the game-theoretic interaction between distinct decision makers, i.e., those investing in power plants and those constructing transmission lines, to be addressed directly. We find that under perfect competition only one of the wind power producers, the one with lower capital cost, makes investment and to a lower degree under a profit-maximising merchant investor (MI) than under a welfare-maximising transmission system operator (TSO), as the MI reduces the transmission capacity to increase congestion rent. In addition, we note that regardless of whether the grid expansion is carried out by the TSO or by the MI, a higher proportion of wind energy is installed when power producers exercise market power. In effect, strategic withholding of generation capacity by producers prompts more transmission investment since the TSO aims to increase welfare by subsidising wind and the MI creates more flow to maximise profit. Under perfect competition, a higher level of wind generation can be achieved only through mandating renewable portfolio standards (RPS), which in turn results also in increased transmission investment.

Contents

List of Acronyms

AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
BONMIN	Basic Open-source Nonlinear Mixed Integer programming
CHP	Combined Heat and Power
CO	Cournot Oligopoly
CP	Central Planner
CVaR	Conditional Value-at-Risk
DER	Distributed Energy Resources
DER-CAM	Distributed Energy Resources Customer Adoption Model
DG	Distributed Generation
EC	European Commission
EEX	European Energy Exchange
ENTSO-E	European Network of Transmission System Operators for Electricity
EPEC	Equilibrium Problem with Equilibrium Constraints
EU	European Union
FTR	Financial Transmission Right
GAMS	General Algebraic Modeling System
GBM	Geometric Brownian Motion
IOU	Investor-Owned Utility
KKT	Karush-Kuhn-Tucker
LP	Linear Programming
MCP	Mixed-Complementarity Problem
MI	Merchant Investor
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MIQP	Mixed-Integer Quadratic Program
MPEC	Mathematical Program with Equilibrium Constraints
MT	Microturbine
NPV	Net Present Value
OECD	Organisation for Economic Co-operation and Development
PC	Perfect Competition
REC	Renewable Energy Credit
RPS	Renewable Portfolio Standard
SMD	Standard Market Design
SW	Social Welfare

TCC	Transmission Congestion Contract
TSO	Transmission System Operator
VaR	Value-at-Risk

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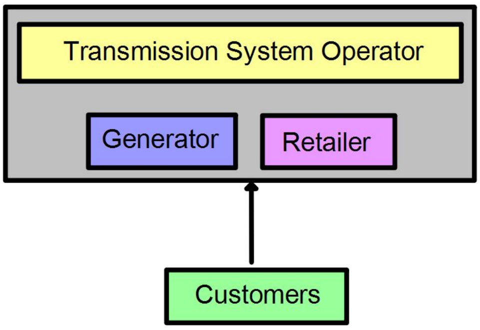
Chapter 1

Introduction

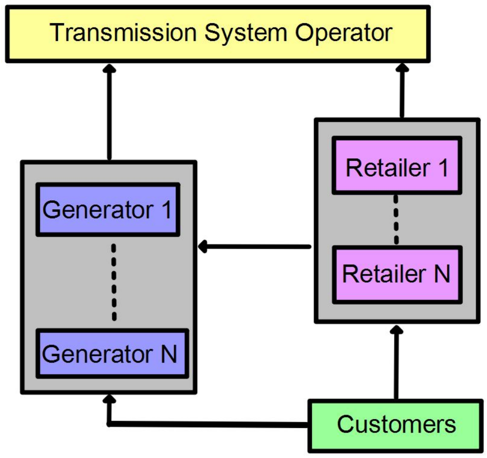
Energy has been at the centre of economic development since the beginning of the Industrial Revolution: for example, coal and oil have had long-established markets and have played an important role in international trade. Not only did coal facilitate the advancement of rail transport, but also coal traffic itself has been a major source of income of the railway industry ever since (Solomon and Yough, 2009). Today, crude oil is the most widely traded commodity in the world, accounting for over 30% of international shipping (Ji and Fan, 2013). Electricity began to be sold publicly not long after the establishment of the first oil refineries and has soon become inseparable from modernity. As a result of increasing electrification of services, electricity improves more and more aspects of life. Indeed, the electric power industry is one of the world's largest industries (Morton, 2002). However, unlike coal and oil, electricity is still provided only by government owned utilities in large parts of the world, and the establishment of competitive wholesale electricity markets is a very recent development.

In the late 19th century, the first power plants were financed completely by private capital. Electricity was supplied through direct current and was used locally, providing street and home lighting. Over the course of time, with the advancement of the applications of alternating current, electricity could be transported over longer distances, thereby triggering the establishment of utility companies. Since building large transmission networks required huge initial investments and power generation exhibited significant economies of scale, the electricity industry was regarded as an ideal example of a natural monopoly. In fact, after the Second World War, electricity systems were nationalised in most OECD countries (Millward, 2005). All functions of the electricity supply chain, i.e., generation, transmission, and distribution, were merged into state-owned utility companies (Finon and Midttun, 2004). These vertically integrated companies built their own power plants and coordinated generation investments with the planning of transmission expansion. In real time, system operators controlled electricity generation by deciding which power plants should operate and which ones need to shut down in order not to overload the transmission network (Hunt, 2002). Since customers paid a single tariff, set by the regulatory authority, for the electricity, unlike in a deregulated industry, the generators received no price signal for efficient operation (Fig. 1.1). This led to highly politicised pricing and investment decisions, where risk management or profitability played little to no role.

However, the energy crisis of the 1970s exposed the inefficiencies within the generation and distribution sectors along with their vulnerability to oil imports (Gibbons and Blair, 1991). Even so, the subsequent years were still marked by strong state control of all energy industries, but this time with a greater focus on new technologies and diversification of the energy mix. In the 1980s, economic policies shifted towards liberalisation, i.e., erasing trade barriers, privatising monopolies, reducing government regulations, and opening up industries to full competition (Rubsamen, 1989). In the electric power industry, where physical constraints precluded full liberalisation, the focus was on deregulating the generation sector end which displayed the most striking inefficiencies, i.e., poor choice of technology, lack of innovation, cost overruns in construction and maintenance, and difficulties in pricing (Joskow, 2000). Also, the political risks of purchasing cheap natural gas from the former Soviet Union were reduced with the end of the Cold War (Helm, 2009). Consequently, the 1990s saw the introduction of several directives from the European Union (EU) with the aim of reducing the barriers to cross-border trade of electricity (Jamasb and Pollit, 2005). In particular, the EU Electricity Market Directives of 1996 and 2003 focused on unbundling the industry and a gradual opening of national markets. The 2003 directive further promoted competition by tightening the regulation of access to networks and enforcing the use of independent regulators. These measures led to restructured electricity industries with increased competition in wholesale generation and retail supply, intensive regulation of distribution networks, and privatisation of regional utility companies (Jamasb, 2002), which, consequently, led to the emergence of modern electricity markets.



(a) Regulated Electricity Industry



(b) Deregulated Electricity Industry

Figure 1.1: Money Flows in the Electricity Industry Before and After Deregulation

However, deregulation and liberalisation have not achieved all of the desired outcomes. The failings of deregulation have resulted in complicated market designs, which, in turn, have led to market power abuse and inefficient investments (Woo et al., 2006). Analysing the effects of deregulation of electricity industries, Hattori and Tsutsui (2004) found that the unbundling of generation from transmission and introduction of a wholesale spot market did not necessarily lower prices and might possibly have resulted in higher prices for residential customers. For example, between 1993 and 2000, gas and coal prices decreased by 50% and 28%, respectively, whereas electricity pool price in England and Wales declined by only 12% (Hunt, 2002). Finally, since the liberalised industries in Europe had inherited surplus capacity from the state-owned systems, policies following the deregulation were directed more at an efficient allocation of the given resources than supporting generation investment (Finon et al., 2004).

Nevertheless, the issue of new investment in electricity generation has acquired a greater urgency. New investment is required to replace the old and phased-out power stations (Nagl et al., 2011) to comply with higher efficiency standards and emerging environmental norms. Indeed, concern about climate change has transformed the environmental debate in Europe. The EU aims to limit the effects of global climate change, which, according to the European Commission (EC), will require long-term stabilisation of CO_2 emissions levels (Fig. 1.2). This has been broken down into two main targets: (1) by 2020, the EU should reduce its CO_2 emissions by 30%, and (2) by 2050 by 60-80%, from the levels in 1990. The EU aims to achieve its CO_2 reduction targets by increasing electricity generation from renewable resources and improving the efficiency of both demand and supply sides. However, while the share of renewable energy has increased in recent years, this has had other impacts on the electricity industry. First, to attract investment in renewable generation, governments have provided generous subsidies that have significantly increased the retail prices of electricity. With feed-in tariffs 10 times higher than the wholesale electricity price, German consumers spent €1.54 billion more on electricity to fund renewable generation in 2001 alone (Wüstenhagen and Bilharz, 2006). Second, a large part of renewable generation, e.g., solar and wind, is intermittent, which means that output cannot be controlled directly as in a gas- or coal-fired power plant. This has increased the volatility of electricity prices as a significant share of the electricity generation has become weather-dependent (Ketterer, 2014; Woo et al., 2011, Sioshansi et al., 2011). While a large amount of wind generation during low demand periods results in low market clearing prices and sporadically in negative prices (Nicolosi, 2010), unexpected ramp-down of wind generation can lead to price jumps and even to system failures (Ela and Kirby, 2008). A higher share of renewable energy in the total generation not only results in volatile electricity prices but also puts a previously unexperienced strain on the transmission network. In an electricity system adhering to the merit-order rule, wind generation with zero marginal cost needs to be dispatched first; however, guaranteeing this grid access to wind energy with fluctuating and geographically dispersed generation leads to scarce electric network supply (Kunz, 2013). Consequently, further growth of intermittent generation, Kramer and Haigh (2009) argue, can even destabilise transmission networks, thereby resulting in blackouts.

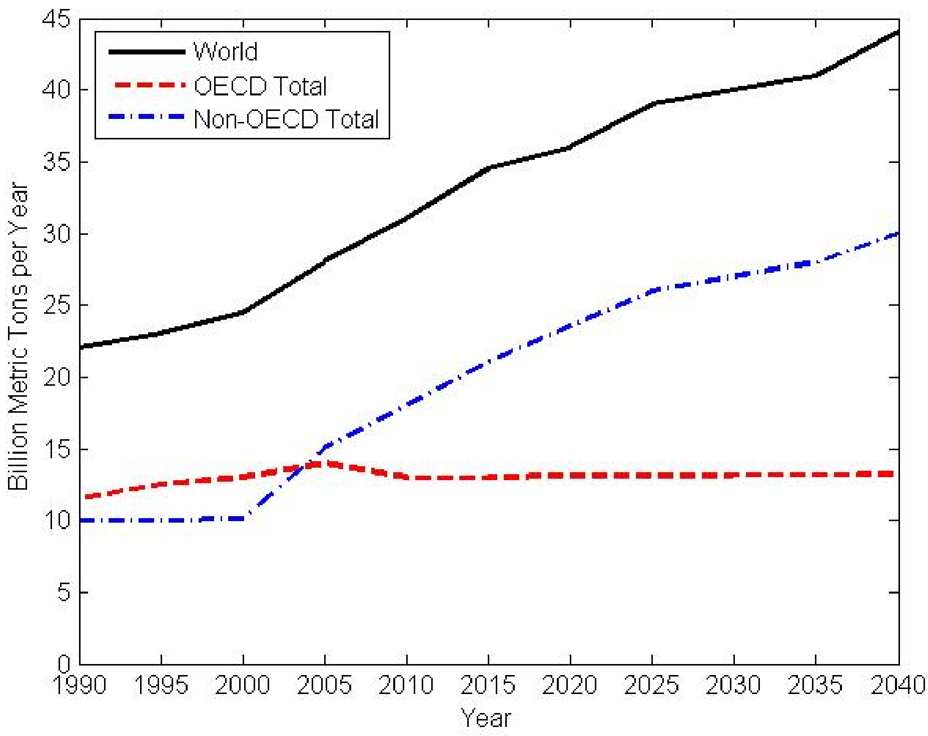


Figure 1.2: Historical and Predicted CO_2 Emissions (IEO, 2013)

Thus, deregulation and the so-called *Energiewende* (German energy transformation) have ushered in undesirable consequences for the electricity industry. Higher price volatility threatens both large consumers, such as factories or hospitals, and producers as they may become more exposed to risk. As a result, there is an urgent need for a more effective risk management and a better understanding of strategic interaction when setting policy. Otherwise, the very objectives of the sustainable energy transformation may be thwarted as private investors become more reluctant to adopt new technologies. One of the main tools for risk management in the electricity industry is the use of derivatives, i.e., financial products whose value depend on physical spot prices. The most liquid derivatives in energy markets are futures contracts (Kovacevic et al., 2013). By entering into a futures contract, i.e., a standardised exchange-traded contract, the counterparties agree on both the price and the time period, stretching from weeks to years, of a sequence of future spot deliveries. For electricity futures, we differentiate between peak, off-peak, and base futures, specifying the delivery hours with high or low demand. The settlement of a contract can be physical (actual delivery) or financial (payment of the difference of the futures price and the spot price). Financial hedging, i.e., purchasing electricity futures, however, can be costly and often does not provide adequate risk reduction. Indeed, futures contracts can have high risk premia, the difference between the expected and futures prices, and the delivery periods seldom match the consumers' demand schedule (Geman, 2009). Furthermore, futures contracts do not provide hedges against physical risk, i.e., power outages, whose financial consequences can outweigh the potential payoffs from futures contracts. In addition to increased price volatility, deregulation and renewable generation have also affected the distribution systems. To integrate more intermittent generation, new transmission lines need to be built, partly because the best available wind and solar sites are in remote areas. Since the vertical unbundling of the electricity industry, the cost of transmission expansion cannot be regained through retailing. Thus, under a market-oriented regulation, transmission investment needs to be economically viable. At the same time, in order to maintain system efficiency, the cost of transmission expansion has to be allocated in such way that it sends correct locational signals for future users (Pérez-Arriaga, 2013). Consequently, grid investment presents serious planning challenges because generation investment decisions incorporating game-theoretic interactions between decision makers in separate sectors are necessary for designing markets to obtain desirable outcomes.

This dissertation addresses these two concerns. First, a pair of studies shows that large consumers can carry out better risk management using on-site generation, i.e., physical hedges. Such on-site generation using CHP applications not only provides for better hedging strategies but also results in lower CO_2 emissions because of higher overall efficiencies relative to large central power plants. Risk-mitigating strategies for on-site investment and operations for long- and medium-term time-frames are provided from the perspective of a large consumer. Next, in order to gain insights into the issues for policy-makers concerning transmission expansion, a bi-level programming model is developed to account for the fact that investment decisions are carried out by separate agents. Thus, any decision regarding transmission investments needs to consider how it would impact future generation investment, which, in turn, would impact system reliability and transmission costs. In particular, the third study focuses on investment in wind energy, which makes up the highest share of renewable generation and has the most volatile production source, implemented through wind output scenarios. Finally, a comparison is made between different market designs, both in terms of transmission expansion and the electricity producers' degree of competitiveness.

1.1 Optimal Selection of Distributed Energy Resources under Uncertainty and Risk Aversion

The probable severe economic and environmental consequences (Stern, 2006; Ciscar et al., 2011) of climate change have prompted many countries to set a series of targets to reduce their CO_2 emissions. One of the ways in which the EU seeks to achieve its reduction targets is by improving energy efficiency in terms of both supply and consumption (European Commission, 2010). There is substantial scope for reducing CO_2 emissions through improved generation technologies. The current central-station model of electricity production causes a loss of 35-60% of energy as heat waste, while a further 6% of the generated electricity is lost during transmission (Marnay and Venkataramanan, 2006; Graus and Worrell, 2009; Oswald, 2007; International Energy Agency Statistics, 2011). Thus, the current energy production paradigm is not only polluting but also unsustainable in the wake of continued growth in demand. One possible solution is the use of distributed energy resources (DER), i.e., small-scale generation sources located closer to the end-users.

An innovative way to exploit the potential of DER is to group generation and associated loads together to form a microgrid (Fig. 1.3). While a microgrid operates independently of the main grid, it can also be connected to it in order to take advantage of lower system prices. Different generators can be used within a microgrid, but the most promising technology is combined heat and power (CHP), also known as cogeneration. CHP is an energy-converting process that utilises thermal energy, which would otherwise be released into the environment unused. While conventional condensing technologies, e.g., central-station fossil-fuelled and biomass-fuelled power stations, produce only electricity from the fuel used, a CHP plant produces both electricity and thermal power with a higher overall energy conversion efficiencies. Thus, even though large central stations have higher electrical conversion efficiencies, CHP plants produce more energy overall because of their heat recovery property (Siddiqui and Marnay, 2008). Compared to the efficiency of 35-60% for conventional power stations, CHP plants have overall efficiencies in the range of 80-90%. Despite the beneficial characteristics of cogeneration, the penetration of CHP plants is relatively low. While in Denmark and Finland CHP plants produce approximately 40-50% of the total electricity from heat recovery, EU and US averages of CHP electricity production are only around 15% and 7%, respectively[1].

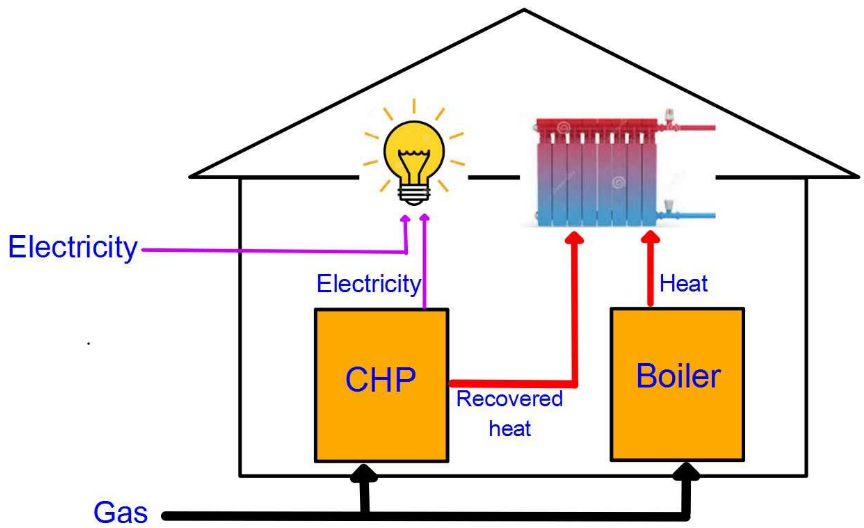


Figure 1.3: Stylised Microgrid with CHP

Nevertheless, the potential of CHP is significant with possible savings of up to 60% in total efficiency. This is why most countries have developed policies to support CHP investment, e.g., the EU Cogeneration Directive dating back to 2004. However, the targets regarding a higher share of cogeneration have not yet been achieved (Streckiene et al., 2009). Some of the possible reasons for the lower than expected investments in CHP are the uncertainties of electricity and gas prices in deregulated industries (European Cogeneration Review - Germany, 2013). Financial risk is considered by Schleich and Gruber (2008) and Wang et al. (2008) as one of the main barriers against investing in energy-efficient technologies.

Considering this situation, in order to gain policy insights into the issues involved in increasing efficiency and reducing CO_2 emissions, it is important to understand how the risks associated with electricity and gas spot price uncertainties can be managed at the consumer level. With this in mind, this study explores the roles of on-site generation (as a physical hedge) and long-term electricity and gas futures contracts (as financial hedges) against energy price risk. A mean-risk optimisation model is developed for the long-term risk management problem of a hypothetical microgrid using mixed-integer, multi-stage stochastic programming. Since the potential of CHP to reduce CO_2 emissions is markedly high in Germany (Spitalny et al., 2013), we apply our model to a notional consumer in

[1] World Survey of Decentralized Energy, www.localpower.org.

Germany by using electricity and gas price data from the European Energy Exchange (EEX). Several cases of different on-site generation technologies are examined both with and without financial hedges. The study demonstrates that risk-averse consumers, even if they face increasing gas prices and decreasing electricity prices, should invest in on-site generation. While a decreasing gas spark spread, which is the difference between the price of electricity and effective cost of electricity generation from a gas-fired power plant, reduces the expected net present value (NPV) of on-site generation investment, the ability of CHP to swap electricity (with high price volatility) for gas (with low price volatility) significantly increases the value of on-site generation as a physical hedge. This study also examines how on-site generation interacts with financial hedges, i.e., how the availability of on-site generation affects the consumer's decision to purchase financial hedges and vice versa. In particular, the study shows that since investing in CHP reduces the microgrid's demand for electricity futures, on-site generation and electricity futures may substitute for one another. Conversely, when gas futures are available, the microgrid is more likely to install a microturbine as on-site generation with fixed fuel price results in larger risk reduction. For this reason, if the the risk premium for gas futures decreases, the risk-averse microgrid's demand increases for on-site generation, thereby indicating that gas futures and on-site generation can function as complements.

1.2 Optimal Operation of Combined Heat and Power under Uncertainty and Risk Aversion

Building on the dissertation's investment model for a microgrid, the medium-term operational risk management problem of a microgrid with installed CHP is further examined. Unlike in the previous investment model, we account for peak and off-peak load electricity price volatility, thereby providing further insights into how financial risk can be mitigated using on-site generation and the available financial contracts for electricity and gas purchases.

Stable electricity prices are vital for economic competitiveness (Laurijssen et al., 2012). Since electricity and gas markets exhibit large volatility, uncontrolled exposure to price risks could lead to severe financial losses for producers and consumers. Thus, operational decisions need to be evaluated in terms of not only the resulting expected costs but also of cost variability (Bjorgan et al., 2009). Consequently, risk control constitutes an important issue when formulating consumers' decision-making problems.

To hedge against such risks, large consumers can purchase electricity futures contracts that provide increased stability compared to spot prices and are more efficient than futures contracts on related fuel prices (Tanlapco et al., 2002). Deng and Oren (2006) highlight the roles of these electricity derivatives in mitigating market risks and structuring the hedging strategies in various risk management applications. On the other hand, Newbery (2012) points out that gas and coal are naturally hedged in markets where the wholesale electricity prices are set by the prices of fossil fuels. For example, if there is a strong positive correlation between the electricity price and the price of natural gas, a gas-fired generator is not burdened by an increase in the gas price as this inevitably triggers higher electricity price, thereby maintaining the generator's profit level. However, as Lin and Wesseh (2013) point out, gas price can exhibit different volatility regimes, and when it switches to a high volatility regime, the correlation between electricity and gas prices significantly diminishes. Consequently, the strategy for managing risk needs to consider both electricity and gas markets uncertainty at the same time. In this study, we present a multi-stage, stochastic mean-risk operational optimisation model that can be used to reduce a microgrid's risk exposure. The model examines natural hedging through existing on-site generation and financial hedging through implementing the available electricity and gas futures purchases in the German context.

While the findings suggest that a microgrid with on-site generation alone can certainly reduce its expected generation costs, a microgrid with CHP can lower the expected costs much more significantly, i.e., on average about 8.7-fold more than a microturbine without heat recovery. Furthermore, on-site generation with CHP can reduce the microgrid's CVaR both in absolute terms and relative to its expected cost, while the CVaR reduction with a conventional microturbine is negligible and only due to lower expected cost. This demonstrates the distinctive capability of a CHP unit to reduce a consumer's risk exposure, which is not apparent from the dissertation's long-term investment model.

1.3 Transmission and Wind Investment in a Deregulated Electricity Industry

In regulated electricity industries, the transmission expansion planning involves minimising investment costs subject to reliability constraints regarding future demand and generation configuration (Georgilakis, 2010). As both generation and transmission investments are made by a central utility, only the future demand remains uncertain and the cost of such expansion projects can be recouped through rate-based revenues, which are composed of the depreciated cost (original cost minus cumulative depreciation) of the existing transmission network plus the forecasted cost of incremental capital expenditure (Lévêque, 2006). Thus, such problems can often be addressed by linear programming or dynamic programming models. In recent years, however, the electricity industry has been undergoing deregulation, thereby creating private power companies and TSOs. Hence, understanding their strategic interactions in handling transmission and generation expansion poses novel modelling challenges (Hobbs, 1995).

The ongoing restructuring of the electricity industry, both domestic and cross-border, has led to a growing attention to transmission capacity expansion, which plays a central role in the EU 2020 plan (Communication from the European Commission, 2014). First, to achieve a common European power market, it is essential to have sufficient cross-border transmission capacities. Such a pan-European integrated energy market would result in lower prices and more reliable supply (Schaber et al., 2012; Concha et al., 2014). Second, grid extensions are necessary for the physical integration of variable renewable energy sources: both wind and solar energy have greater potential on the periphery of Europe, and, thus, integrating them would require the construction of new transmission lines both within and between countries (Boie et al., 2014). However, it is not always in the interest of TSOs to upgrade their grid networks since increasing transmission capacity reduces their ability to charge for transmitting electricity (Hogan et al., 2010), or even if they have sufficient incentives to invest, then TSOs might not have the required capital to build new transmission lines (Henriot, 2013). Similarly, investor-owned utility (IOU) companies cannot be expected to make future investments estimated to be worth €1 trillion (Communication from the European Commission, 2014), which is roughly twice as much as the market capitalisation of all European utility companies (The Economist, 2013).

One approach to the problem of transmission expansion in deregulated industries is performance-based regulation (PBR), or incentivised regulation, which is characterised by two main properties: it gives a regulated firm the choice of prices for its services and it rewards the firm for investments that enhance the general welfare. Thus, its aim is to create a price regulation mechanism that incentivises both effective capacity utilisation and capacity expansion for the transmission system operator (TSO). However, because of the information asymmetry between the regulator and TSOs, the specified transmission costs and rewards often fail to provide correct signals, thereby leading to suboptimal transmission and generation investments (Nasser, 1997; Vogelsang, 2006). Yu et al. (1999) have examined the problem of dynamic decision making for transmission management under deregulation. They conclude that transmission congestion rents are necessary to prevent the network from overloading and could serve as the basis for developing a uniform approach to long-term transmission investment incentives.

Another approach is the merchant model, which is built on the idea of using market incentives instead of central planning decisions whenever possible. The merchant model is based on the auction of financial transmission rights (FTRs). Agents bid for transmission expansion, and the winning bidder is allocated long-term FTRs in exchange for the investment. The FTRs give the owners the right to collect the difference in the connecting nodal prices calculated by the TSO, whose role is to balance the supply and demand in the whole network. FTRs are most commonly used in the Northeastern US, but they have been also applied in several European projects. Nevertheless, because of their complexity, it is very difficult to design FTRs efficiently. Bushnell and Stoft (1997) recommend the use of feasibility restrictions and tradable transmission rights, such as transmission congestion contracts (TCCs), which not only would guarantee the profit coming from the difference of the nodal prices when electricity is transferred but also would be refunded for the unused portion of this right. Furthermore, in discussing the positive and negative externalities of building a line, they point out that TCCs do not necessarily capture the full range of benefits of the grid expansion. The difficulties arise mainly from loop flows: in accordance with Kirchoff's second circuit law, the directed sum of voltages around any closed circuit must be zero. For example, in a 3-node network, the voltages at two nodes determine the voltage at the remaining node (Fig. 1.4). Therefore, the way the electricity reaches the load depends on the potential differences. Hence, in a transmission network with multiple circuits, electricity flow does not necessarily go through the newly built line.

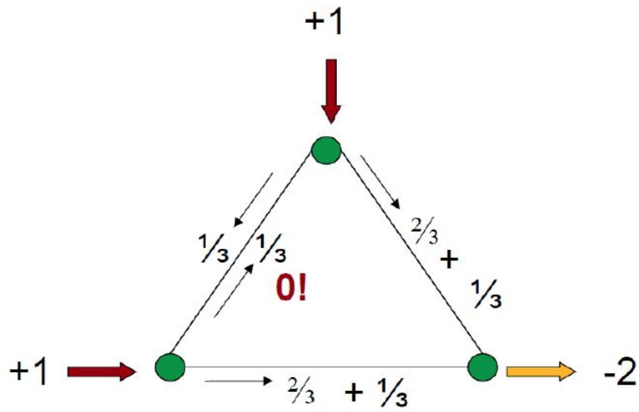


Figure 1.4: Voltage Law (Huppmann and Kunz, 2011)

Our third study addresses the transmission expansion problem in a deregulated industry. Market designs are compared with either a welfare-maximising TSO or a profit-maximising merchant investor (MI) via a stochastic bi-level programming model that has either the TSO or the MI making transmission investment decisions at the upper level, and power producers determining generation investment and operation at the lower level while facing wind power variability. The findings suggest that social welfare is always higher under the TSO because the MI has an incentive to boost the congestion rents, i.e., the scarcity rent on the lines, by restricting the capacities of transmission lines. Such strategic behaviour also limits investment in wind power by producers. However, regardless of the market design (MI or TSO), when producers behave according to the Cournot conjecture, a higher proportion of energy is produced by wind. In effect, withholding of generation capacity by producers prompts more transmission investment since the TSO aims to increase welfare by subsidising wind power and the MI creates more flow to maximise profits.

1.4 Structure of the Thesis

The remainder of the thesis is structured as follows. In Chapter 2, a mean-risk optimisation model is developed for the long-term risk management problem of a hypothetical microgrid using mixed-integer, multi-stage stochastic programming. The modelled microgrid can invest in a number of generation technologies and also has access to electricity and gas futures markets to reduce its financial risk. Chapter 3 assesses how a microgrid with an installed CHP and a boiler unit can manage risk using monthly and weekly electricity futures contracts, monthly gas futures contracts, and on-site generation. A multi-stage, mean-risk optimisation model is formulated for the medium-term operational risk management of a large consumer using daily peak and off-peak periods. Chapter 4 considers the problems of both wind generation and transmission line investment. A stochastic bi-level programming model is developed to examine how transmission expansion interacts with the strategic behaviour of the incumbent electricity producers and potential wind energy investors facing uncertain wind availability. Chapter 5 concludes with a discussion on the findings as well as the limitations of the current approaches besides making recommendations for future research in these areas.

Chapter 2

Optimal Selection of Distributed Energy Resources under Uncertainty and Risk Aversion

2.1 Introduction

Due to a combination of recent deregulation and technological advances in small-scale generation, such as the pairing of proton exchange membrane fuel cells with combustion turbines (Arsalis at al., 2011), consumers now have the opportunity to reap the benefits of small-scale electricity generation. However, uncertain electricity and gas prices often deter potential investors from installing on-site generation. This represents a missed opportunity for the electricity industry in terms of improved sustainability. Although policymakers have set ambitious targets, decisions relating to the adoption of new technologies are typically made by power companies and large consumers, e.g., residential estates, office buildings, and factories, who are motivated by their own private incentives to maximise profit or to minimise cost.

Since the late 1980s, policymakers have gradually deregulated electricity industries with the intention of increasing competition between producers (Wilson, 2002). Consequently, the 1990s saw the introduction of several directives from the EU that sought to extend the single market principle to the electricity market (Jamasb and Pollitt, 2005). However, deregulation often resulted in flawed market designs, which led to market power abuse and spot price volatility (Woo et al., 2006). In addition, in Europe, intermittent generation has increased more than five fold since 2002[1], thereby resulting in more frequent price jumps and negative electricity prices, as well, while the gas price has been affected by political uncertainties in Ukraine (Chow and Elkind, 2009; Goldthau and Boersma, 2014). As a result of such market uncertainties, energy producers and con-

[1]Energy statistics. http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Renewable_energy_statistics

sumers face increased exposure to financial risk, which affects their decisions to launch new projects. Yet, new investments are required to replace inefficient technologies with high CO_2 emissions, which must be done in order to meet increasing electricity demands.

Considering this situation, in order to gain policy insights about increasing efficiency and reducing CO_2 emissions, it is important to understand how the risk associated with electricity and gas spot price uncertainty can be managed at the consumer level. With this in mind, we discuss, in relation to a hypothetical microgrid, the development of a mean-risk optimisation model for DG adoption under uncertainty using mixed-integer multi-stage stochastic programming. While microgrid systems may employ a wide range of distributed energy technologies, e.g., microturbines, solar photovoltaic (PV) panels or micro-scale wind turbines (Fig. 2.1), for now, we assume that the microgrid can use only gas-fired combustion engines, and it applies advanced controls to manage its loads and to connect to the main grid if it is necessary or favourable. We explore the roles of on-site generation as a physical hedge and electricity and gas futures contracts as financial hedges against energy price risk. We examine several cases of different on-site generation technologies both with and without financial hedges. We demonstrate that risk-averse consumers, even if they face increasing gas prices and a decreasing electricity prices, should invest in on-site generation to meet their electricity and heating demands. While a decreasing gas spark spread, the estimated gross margin of a gas-fired power plant from selling a unit of electricity, reduces the expected NPV of on-site generation investment, the ability of CHP to swap electricity (with high price volatility) for gas (with low price volatility) increases the value of on-site generation as a physical hedge significantly. We also examine how on-site generation interacts with financial hedges, i.e., how the availability of on-site generation affects the consumer's decision to purchase financial hedges and vice versa. In particular, we show that, while on-site generation and electricity futures may substitute one another, on-site generation and gas futures can function as complements.

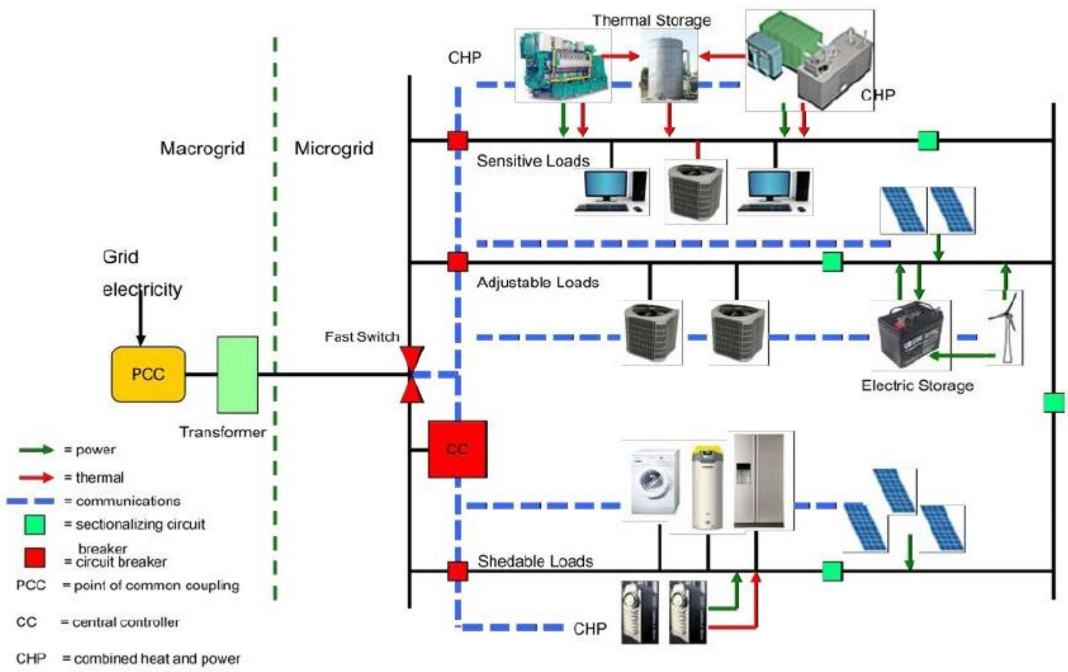


Figure 2.1: Schematic Diagram of a Microgrid (New York State Report, 2012)

2.2 Literature Review

The benefits of on-site generation and CHP have been analysed using deterministic, real options, and stochastic programming approaches. From a deterministic perspective, Madlener and Schmid (2003) examine the economic adoption and diffusion of CHP generation. They find significant regional differences in the adoption of CHP technologies, which could not be explained by NPV calculations. To study the economics of microgrids, the Berkeley Lab has developed the distributed energy resources customer adoption model (DER-CAM), which provides decision support for individual customer sites (Marnay et al., 2001; Siddiqui et al., 2003). The main objective of the model is to find the combination of generation investments with the lowest operational cost given utility tariffs, fuel costs, CO_2 tax rate, and equipment performance characteristics (Fig. 2.2). Siddiqui et al. (2005) use DER-CAM to compare the economic benefit of installing different types of DER at a hypothetical microgrid in California. Using mixed-integer linear programming, they demonstrate that an optimally run microgrid with gas-fired CHP turbines has, on average, lower CO_2 emissions than microturbines without heat exchangers. Siddiqui et al. (2007) analyse the conditions under which a microgrid with CHP is profitable, particularly when also equipped with heat storage technology. Siler-Evans et al. (2011) investigate why the adoption of small-scale distributed generation (DG) has been slow, despite its frequently cited benefits. They find that uncertainty in future fuel and electricity prices represents significant economic risk and suggest feed-in tariffs for its mitigation.

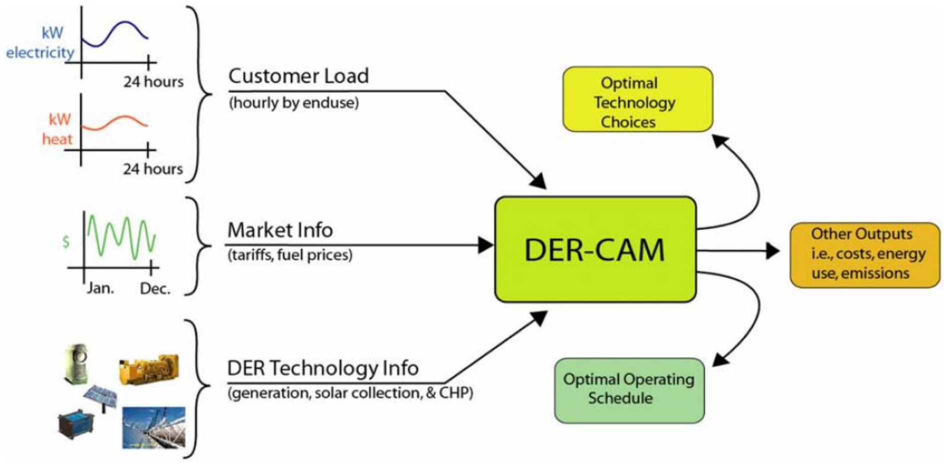


Figure 2.2: High-Level Schematic of the Inputs and Outputs of DER-CAM. (Marnay et al., 2008)

Addressing the uncertainty of electricity prices, Fleten et al. (2007) apply real options valuation to investments in decentralised renewable power generation. Results from a case of wind power generation for an office building suggest that, within the context of uncertain electricity prices, the threshold price for investment is higher than the NPV break-even price. Maribu and Fleten (2008) use Monte Carlo simulation to estimate the value of CHP under uncertain electricity and natural gas prices. They find that cogeneration is particularly attractive with volatile electricity prices because the CHP plant's ability to respond to high prices provides efficient hedges to energy cost risk. Wickart and Madlener (2007) use real options to analyse an industrial firm's choice to invest in a CHP system over a conventional heat-only generation system (steam boiler) with all electricity purchased from the grid. They argue that under higher price volatility levels, the CHP system is a better choice than the conventional heat-only generation. Siddiqui and Maribu (2009) examine the effects of a sequential strategy on the investment decision of a microgrid when capacity and heat exchange upgrade options are available. They conclude that a direct investment strategy is preferred with a combined distributed generation and heat exchange system compared to the sequential strategy due to the cost savings from heat production and capture.

Although the real options approach can be used to analyse investment under uncertainty, it does not lead to better decision making in terms of risk reduction. Stochastic programming provides a more appropriate framework for modelling decision-making problems under uncertainty. Unlike deterministic optimisation models, stochastic programming models encompass uncertain problem data in the form of a random matrix with estimated probability distribution. In general, stochastic programs can be grouped into recourse problems and chance-constrained problems. Chance-constrained problems involve only here-and-now decisions, i.e., all decisions are taken simultaneously prior to the realisation of uncertain parameters. Furthermore, in chance-constrained problems, constraints involving random parameters must be satisfied with only a prescribed probability. In contrast to chance-constrained problems, in recourse problems, all constraints need to be satisfied with certainty, which allows for corrective actions to be taken at future stages once uncertain parameters are observed. Since, unlike real options, a risk term can be easily incorporated in the objective function, stochastic programming with recourse is the most suitable framework to analyse risk management. Its objective is to find a feasible solution that optimises a cost function that depends on decisions and uncertain parameters. In problems related to energy, various constraints, e.g., demand or capacity constraints, need to be satisfied with certainty. Thus, in this study, we consider only stochastic programming with recourse. For a general description of stochastic programming, see Kall and Wallace (1994), and Birge and Louveaux (1997).

Since the deregulation of the electricity industry, stochastic programming has been widely applied within the power sector. Fleten and Kristoffersen (2007) compare stochastic programming and deterministic approaches to the bidding strategies of a Norwegian hydropower producer. They find that using a stochastic programming model is, on average, more profitable than using the solution of the deterministic approach. The deterministic model can lead to huge losses if the realised price differs from the price for which the model is optimised. Also, the solution of the stochastic programming model is more robust as it takes various price scenarios into account. Kettunen et al. (2011) analyse the impact of carbon price uncertainty on investments in the energy sector. Using a multi-stage stochastic optimisation model, they find that carbon price shocks deter smaller companies and that current carbon policies may, therefore, result in market concentration.

We apply stochastic programming to the CHP investment problem of a microgrid, which has been examined previously using only deterministic models and real options. Analogous to Wickart and Madlener (2007), we take the perspective of a large consumer facing uncertain fuel and electricity prices, but our study also provides insights into the interaction of financial hedges and on-site generation focusing on a microgrid's risk management. Finally, we report on how different technologies can contribute to reaching the 2020 CO_2 emissions targets.

2.3 Model Description

Our model addresses the investment problem of a hypothetical commercial microgrid with electricity and heat loads. Initially, the microgrid consists only of a gas-fired boiler, but it has the option to invest in microturbines, with or without heat exchangers, at the beginning of the time horizon. If this option is not exercised, then the microgrid can meet its electricity loads only through purchasing electricity on the spot and futures markets.

Similarly, without CHP, the microgrid covers all of its heat loads by purchasing gas on the spot and futures markets for its boiler. To begin with, we assume that both electricity and gas and futures contracts are physically settled. If a microturbine without a heat exchanger is installed, then the microgrid can meet its electricity demand with on-site generation, for which the gas is purchased on the spot and futures markets. On the other hand, if CHP is installed, then the microgrid also has the possibility to recover the heat waste from its electricity generation and utilise it to supply its heat loads. The energy flows with different technologies are indicated in Fig. 2.3.

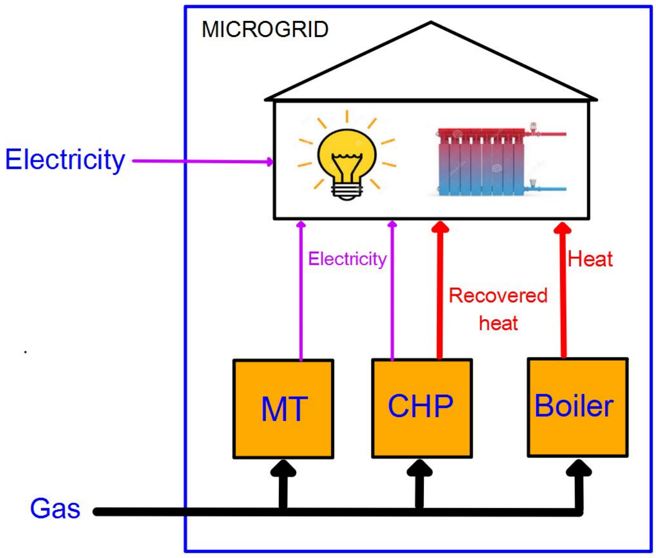


Figure 2.3: Stylised Microgrid with CHP

We assume that the microgrid is a price taker and that it faces uncertain electricity and gas spot prices. By contrast, since energy loads in commercial buildings can be forecast with high accuracy (Zhao and Magoulès, 2012), we assume that both electricity and heat loads are known in advance. Thus, the microgrid makes its investment and futures contracting decisions without knowing spot price realisations, but it can purchase additional electricity and gas later when their spot prices are known. Therefore, the microgrid's investment problem can be formulated using mixed-integer multi-stage stochastic programming with recourse. To take into account possible risk preferences, we assume that the microgrid's objective is to minimise its expected cost plus a risk measure with weight B. For the risk measure, we use the conditional value-at-risk (CVaR), which estimates the expected loss with a confidence level $A \in [0, 1)$ in the worst $1 - A$ cases (Fig. 2.4). CVaR is formulated with the help of the value-at-risk (VaR), which defines losses at the A percentile. As VaR is a threshold value, i.e., the probability that the loss exceeds this value is $1 - A$, in contrast to CVaR, it does not provide any information regarding the size of loss beyond this level. In addition, unlike VaR, CVaR is a coherent risk measure, i.e., it does not violate the sub-additivity property. The CVaR of a portfolio of different assets is always less than the sum of CVaRs of all assets independently. Finally, as CVaR can be formulated using linear programming, it is suitable for optimisation problems (Artzner et al., 1999; Rockafellar and Uryasev, 2000). Thus, we apply CVaR to examine different regimes for the microgrid in terms of risk aversion, such as $B = 0$ for risk neutral and $B > 0$ for risk averse.

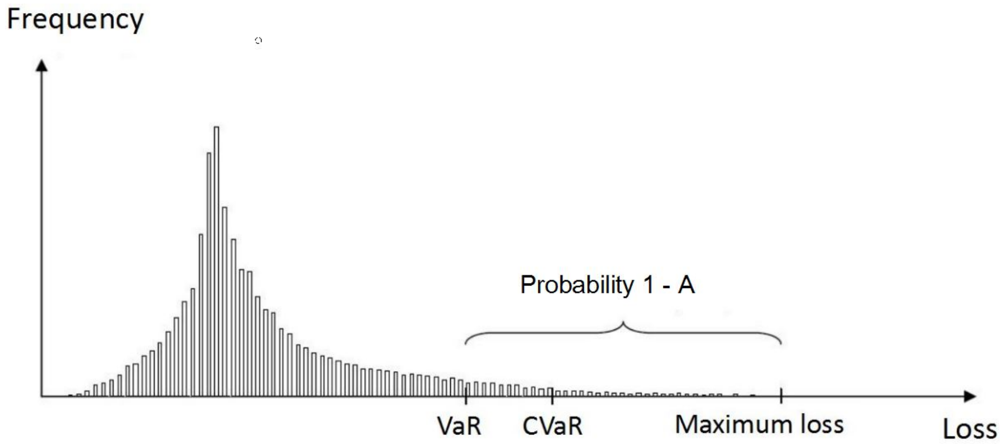


Figure 2.4: CVaR in Relation to VaR

2.3.1 Decision-Making Framework

The time horizon of the optimisation problem is divided into main periods indexed by $t \in \mathcal{T} := \{1, ..., T\}$, each of which is split into subperiods, indexed by $m \in \mathcal{M} := \{1, ..., M\}$ (see Fig. 2.5). The decision to invest in on-site generation has to be made at the beginning of the first main period, i.e., at $t = 1$, and is effective immediately. At the beginning of every main period, the microgrid can decide to reduce its risk exposure by purchasing electricity and gas futures. Subsequently, the microgrid can adjust its futures purchases by going on the spot market to purchase electricity and gas at their realised prices in each subperiod within that main period. Similarly, the microgrid also decides at each subperiod how much electricity to generate. After the last subperiod, a new main period starts, in which all decisions on futures and spot purchases are repeated.

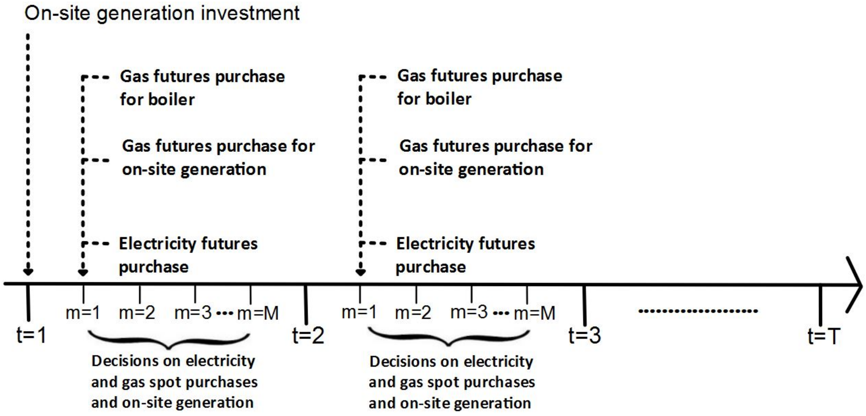


Figure 2.5: Decision-Making Timeline

2.3.2 Problem Formulation

The microgrid's investment problem is formulated as a mixed-integer stochastic program, in which the objective is to minimise the expected present value of its cost plus the CVaR with B weight. Because of the stochastic and combinatorial nature of these problems, solving a mixed-integer stochastic program can lead to computational difficulties. This is why it is essential to test and compare the results of multiple solvers and algorithms when we attempt to solve such a problem. The notation and the mathematical formulation are stated below. The uncertain price processes are represented through a combination of a scenario tree (main scenarios) and scenario fans (subscenarios). The detailed scenario generation method is provided in Section 2.4.1. An essential part of the problem formulation in stochastic programming models is the implementation of the non-anticipativity principle, i.e., decisions need to be taken without knowing in advance the future outcomes. Thus, note that the investment decision (w_i) is the same in every main scenarios and subscenarios, whereas the futures purchase decisions ($x^{\mathrm{f}}_{s_1^t}$,$y^{\mathrm{f}}_{s_1^t}$, $z^{\mathrm{f}}_{s_1^t}$) are the same for each subscenario at a main scenario node, thereby guaranteeing that the non-anticipativity conditions for both the investment decisions and futures purchases are satisfied, Eqs. (2.9)–(2.11).

2.3.3 Notation

Sets

$b(s_1^t) \in \mathcal{S}_1^{t-1}$: ancestor to path s_1^t
$i \in \mathcal{I}$: technology index
$\mathcal{I}$: set of technologies
m: subperiod index, $m = 1, \ldots, M$
$s_1^t \in \mathcal{S}_1^t$: the index of a particular main scenario path in the scenario tree at main time period t
$\mathcal{S}_1^t$: set of all possible main scenario paths in the scenario tree at main time period t
$s_2 \in \mathcal{S}_2$: the index of a particular subscenario path
$\mathcal{S}_2$: set of all possible subscenario paths at a a given node in the scenario tree
t: main time period index, $t = 1, \ldots, T$

Fixed Parameters

A: confidence level for the CVaR
B: weight of CVaR
C: CO_2 emissions rate of the microgrid from burning gas on-site (ton of CO_2/MWh)
D^{e}: electricity load in each subperiod ($\mathrm{MW_e}$)
D^{h}: heat load in each subperiod (MW)

E^{b}: boiler conversion efficiency, i.e., units of useful heat produced from one MWh of natural gas (MWh/MWh)

E_i^{e}: electrical conversion efficiency, i.e., units of electricity produced from one MWh of natural gas, of technology i (MWh$_\mathrm{e}$/MWh)

E_i^{h}: heat capture rate from CHP, i.e., units of useful heat produced from one MWh$_\mathrm{e}$ of electricity, of technology i (MWh/MWh$_\mathrm{e}$)

H_o: length of each main period in years (a)

H_q: length of each subperiod in years (a)

$J = 8760$: number of hours in a year (h/a)

K_i^{e}: capacity of electricity generation unit of technology i (MW$_\mathrm{e}$)

K^{b}: capacity of boiler unit (MW)

L^{c}: tax on CO_2 emissions (€/ton)

N_i: the amortised cost over $T \times M$ subperiods of installing technology i, paid per subperiod (€)

$Q_{s_1^t}$: probability of main scenario path s_1^t at main time period t

Q_{s_2}: conditional probability of subscenario path s_2 within a particular main scenario

R: risk-free interest rate per annum

V^{e}: variable operating and maintenance (O&M) cost of electricity generation (€/MWh)

Random Parameters

$F_{s_1^t}^{\mathrm{e}}$: multi-subperiod-ahead forward price of electricity purchased during main scenario s_1^t at the beginning of main period t and delivered in all subscenario paths s_2 and in each subperiod m within this main scenario path and main time period (€/MWh$_\mathrm{e}$)

$F_{s_1^t}^{\mathrm{g}}$: multi-subperiod-ahead forward price of natural gas purchased during main scenario s_1^t at the beginning of main period t and delivered in all subscenario paths s_2 and in each subperiod m within this main scenario path and main time period (€/MWh)

$P_{s_1^t,s_2,m}^{\mathrm{e}}$: spot price of electricity in scenario path s_1^t in main period t and in subscenario path s_2 at subperiod m (€/MWh$_\mathrm{e}$)

$P_{s_1^t,s_2,m}^{\mathrm{g}}$: spot price of gas in scenario path s_1^t in main period t and in subscenario path s_2 at subperiod m (€/MWh)

2.3.4 Decision Variables

$\gamma_{s_1^t}$: present value of the cumulative cost of satisfying the electricity and heat loads in main scenario path $s_1^t \in \mathcal{S}_1^t$ up until main period t (€)

$\eta_{s_1^t}$: auxiliary variable in main scenario path $s_1^t \in \mathcal{S}_1^t$ during main period t to calculate the CVaR, it is equal to the amount of cumulative cost, $\gamma_{s_1^t}$, which exceeds the VaR, and it is equal to 0 if the cumulative cost is smaller than the VaR (€)

ξ: VaR at confidence level A (€)

$\varpi_{s_1^t}$: the expected present value at beginning of main period t of the spot operational and amortised capital cost of all subperiods m during main period t

$\Phi_{s_1^t}$ the total cost of purchasing futures for the microgrid in scenario path $s_1^t \in \mathcal{S}_1^t$ at the beginning of main period t (€)

Ψ: the total amortised capital cost for the selected technologies (€)

$\Omega_{s_1^t,s_2,m}$: the total spot operational cost of the microgrid in scenario path $s_1^t \in \mathcal{S}_1^t$ during main period t and in subscenario path $s_2 \in \mathcal{S}_2$ during subperiod m (€)

$h_{i,s_1^t,s_2,m}$: recovered heat from technology i used to meet heat load in main scenario path $s_1^t \in \mathcal{S}_1^t$ during main period t and in subscenario path $s_2 \in \mathcal{S}_2$ during subperiod m (MWh)

w_i: binary variable, now-or-never decision to install technology i at $t = 1$

$x_{s_1^t,s_2,m}$: electricity purchased from the spot market in main scenario path $s_1^t \in \mathcal{S}_1^t$ during main period t and in subscenario path $s_2 \in \mathcal{S}_2$ during subperiod m ($\mathrm{MWh_e}$)

$x^{\mathrm{f}}_{s_1^t}$: electricity futures purchased at main scenario path $s_1^t \in \mathcal{S}_1^t$ at the beginning of main period t, which are divided into equal quantities that are delivered in all subscenario paths $s_2 \in \mathcal{S}_2$ in each subperiod m ($\mathrm{MWh_e}$)

$y_{i,s_1^t,s_2,m}$: natural gas purchased from the spot market for cogeneration in technology i in main scenario path $s_1^t \in \mathcal{S}_1^t$ during main period t and in subscenario path $s_2 \in \mathcal{S}_2$ during subperiod m (MWh)

y^{f}_{i,s_1^t}: natural gas futures purchased for cogeneration in technology i for delivery in main scenario path $s_1^t \in \mathcal{S}_1^t$ at the beginning of main period t, which are divided into equal quantities that are delivered in all subscenario paths $s_2 \in \mathcal{S}_2$ in each subperiod m (MWh)

$z_{s_1^t,s_2,m}$: natural gas purchased from the spot market for boiler in main scenario path $s_1^t \in \mathcal{S}_1^t$ during main period t and in subscenario path $s_2 \in \mathcal{S}_2$ during subperiod m (MWh)

$z^{\mathrm{f}}_{s_1^t}$: natural gas futures purchased for boiler for delivery in main scenario path $s_1^t \in \mathcal{S}_1^t$ at the beginning of main period t, which are divided into equal quantities that are delivered in all subscenario paths $s_2 \in \mathcal{S}_2$ in each subperiod m (MWh)

2.3.5 Mathematical Formulation

Objective Function

The objective function in Eq. (2.1) minimises the expected present value of the microgrid (first term) plus a weighted CVaR of the cost (second term):

$$\underset{\mathbf{h},\mathbf{w},\mathbf{x},\mathbf{y},\mathbf{z},\mathbf{x}^{\mathrm{f}},\mathbf{y}^{\mathrm{f}},\mathbf{z}^{\mathrm{f}},\xi,\eta}{\text{minimise}} \sum_{s_1^T \in\, \mathcal{S}_1^T} Q_{s_1^T}\gamma_{s_1^T} + B\left(\xi + \frac{1}{1-A}\sum_{s_1^T \in \mathcal{S}_1^T} Q_{s_1^T}\eta_{s_1^T}\right) \tag{2.1}$$

Constraints

Eqs. (2.2)–(2.3) define the CVaR constraint of the present value of the cumulative cost of running the microgrid, $\forall s_1^T \in \mathcal{S}_1^T$. Since the auxiliary variable, $\eta_{s_1^t}$, is nonnegative, the term $\xi + \frac{1}{1-A}\sum_{s_1^T \in \mathcal{S}_1^T} Q_{s_1^T}\eta_{s_1^T}$ is only minimised in (2.1), if the VaR, ξ, is exactly the cost at A quantile, as any decrease (increase) in the value of ξ would not be offset by the decrease (increase) in the value of $\frac{1}{1-A}\sum_{s_1^T \in \mathcal{S}_1^T} Q_{s_1^T}\eta_{s_1^T}$, thereby concurrently determining the VaR and the expected loss beyond the VaR, and, hence the CVaR:

$$\gamma_{s_1^T} - \xi - \eta_{s_1^T} \leq 0 \tag{2.2}$$

$$\eta_{s_1^T} \geq 0 \tag{2.3}$$

The constraint in Eq. (2.4) updates the present value of the cost of energy provision:

$$\gamma_{s_1^t} = \begin{cases} \varpi_{s_1^t} + \Phi_{s_1^t} & \text{if } t = 1 \\ \gamma_{b(s_1^t)} + (1 + RH_{\mathrm{q}})^{-(t-1)M}(\varpi_{s_1^t} + \Phi_{s_1^t}) & \text{otherwise, } \forall s_1^t \in S_1^t \end{cases} \tag{2.4}$$

The constraint in Eq. (2.5) calculates the expected present value at the beginning of the main period t for all spot operational and amortised capital cost within main period t, $\forall s_1^t \in \mathcal{S}_1^t$:

$$\varpi_{s_1^t} = \sum_{s_2 \in \mathcal{S}_2} Q_{s_2} \left(\sum_{m=1}^{M} (1 + RH_{\mathrm{q}})^{-m} (\Psi + \Omega_{s_1^t, s_2, m}) \right) \tag{2.5}$$

Eqs. (2.6)–(2.8) give the amortised capital, futures, and spot operational costs, respectively, $\forall s_1^t \in \mathcal{S}_1^t, \forall s_2 \in \mathcal{S}_2, \forall t, \forall m$:

$$\Psi = \sum_{i \in \mathcal{I}} w_i N_i \tag{2.6}$$

$$\Phi_{s_1^t} = \sum_{i \in \mathcal{I}} (F^{\mathrm{g}}_{s_1^t} + V^{\mathrm{e}} + L^{\mathrm{c}}C) y^{\mathrm{f}}_{i,s_1^t} + F^{\mathrm{e}}_{s_1^t} x^{\mathrm{f}}_{s_1^t} + (F^{\mathrm{g}}_{s_1^t} + L^{\mathrm{c}}C) z^{\mathrm{f}}_{s_1^t} \tag{2.7}$$

$$\Omega_{s_1^t,s_2,m} = \sum_{i \in \mathcal{I}} (P^{\mathrm{g}}_{s_1^t,s_2,m} + V^{\mathrm{e}} + L^{\mathrm{c}}C) y_{i,s_1^t,s_2,m} + P^{\mathrm{e}}_{s_1^t,s_2,m} x_{s_1^t,s_2,m} + (P^{\mathrm{g}}_{s_1^t,s_2,m} + L^{\mathrm{c}}C) z_{s_1^t,s_2,m} \tag{2.8}$$

Eqs. (2.9)–(2.10) ensure that the electricity and heat demands are met, respectively,

$\forall s_1^t \in \mathcal{S}_1^t, \forall s_2 \in \mathcal{S}_2, \forall t, \forall m$:

$$x_{s_1^t,s_2,m} + \frac{x^{\mathrm{f}}_{s_1^t}}{M} + \sum_{i\in\mathcal{I}} E_i^{\mathrm{e}} \left(y_{i,s_1^t,s_2,m} + \frac{y^{\mathrm{f}}_{i,s_1^t}}{M} \right) \geq D^{\mathrm{e}} H_{\mathrm{q}} J \tag{2.9}$$

$$\sum_{i\in\mathcal{I}} h_{i,s_1^t,s_2,m} + E^{\mathrm{b}} \left(z_{s_1^t,s_2,m} + \frac{z^{\mathrm{f}}_{s_1^t}}{M} \right) \geq D^{\mathrm{h}} H_{\mathrm{q}} J \tag{2.10}$$

Eq. (2.11) restricts the use of recovered heat, $\forall i \in \mathcal{I}, \forall s_1^t \in \mathcal{S}_1^t, \forall s_2 \in \mathcal{S}_2, \forall t, \forall m$:

$$h_{i,s_1^t,s_2,m} \leq E_i^{\mathrm{h}} E_i^{\mathrm{e}} \left(y_{i,s_1^t,s_2,m} + \frac{y^{\mathrm{f}}_{i,s_1^t}}{M} \right) \tag{2.11}$$

Eqs. (2.12)–(2.13) ensure that the DER and boiler capacity limits are observed, respectively, $\forall s_1^t \in \mathcal{S}_1^t, \forall s_2 \in \mathcal{S}_2, \forall t, \forall m$:

$$E_i^{\mathrm{e}} \left(y_{i,s_1^t,s_2,m} + \frac{y^{\mathrm{f}}_{i,s_1^t}}{M} \right) \leq w_i K_i^{\mathrm{e}} H_{\mathrm{q}} J, \forall i \in \mathcal{I} \tag{2.12}$$

$$E^{\mathrm{b}} \left(z_{s_1^t,s_2,m} + \frac{z^{\mathrm{f}}_{s_1^t}}{M} \right) \leq K^{\mathrm{b}} H_{\mathrm{q}} J \tag{2.13}$$

Finally, all decision variables must be non-negative, $\forall i \in \mathcal{I}, \forall s_1^t \in \mathcal{S}_1^t, \forall s_2 \in \mathcal{S}_2, \forall t, \forall m$:

$$h_{i,s_1^t,s_2,m} \geq 0, w_i \in \{0,1\}, x_{s_1^t,s_2,m} \geq 0, y_{i,s_1^t,s_2,m} \geq 0, z_{s_1^t,s_2,m} \geq 0, x^{\mathrm{f}}_{s_1^t} \geq 0, y^{\mathrm{f}}_{i,s_1^t} \geq 0, z^{\mathrm{f}}_{s_1^t} \geq 0 \tag{2.14}$$

2.4 Numerical Examples

2.4.1 Data and Cases

While Europe has a relatively high level of CHP production, e.g., more than 50% of Denmark's power generation comes from CHP (European Cogeneration Review, 2013), the potential for further CHP implementation is substantial. For example, Golbach (2013) estimates that over 50% of the Germany's total electricity demand could be provided through CHP. Accordingly, Germany has passed three different legislations since 2002 promoting the adoption of CHP with the aim to increase its rate of cogeneration from the

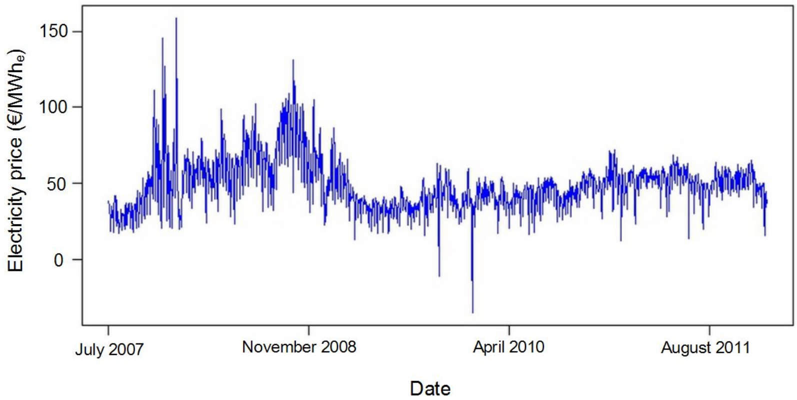


Figure 2.6: Daily Average Electricity Price

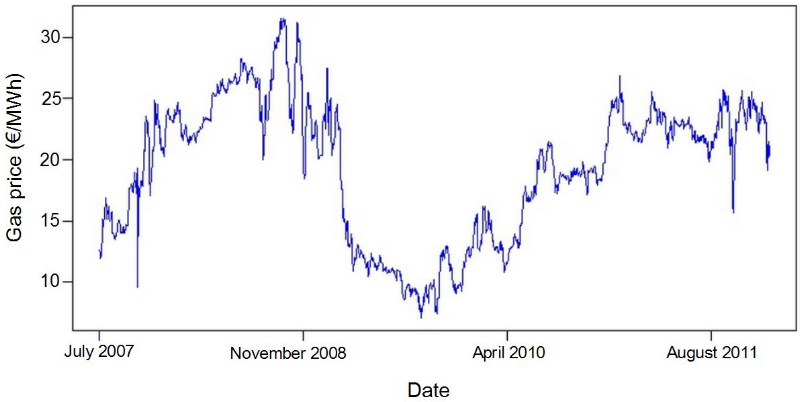


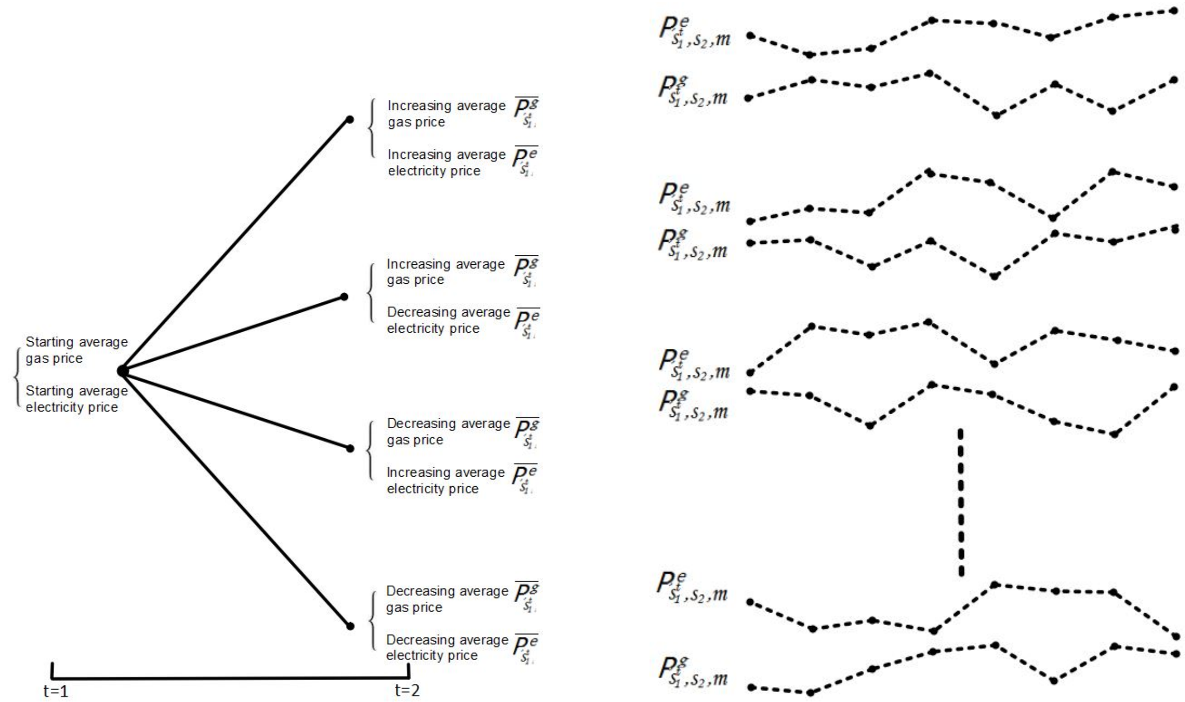
Figure 2.7: Daily Average Gas Price

current level of 14.5% to 25% by 2020 (Kraft-Wärme-Kopplungs-Gesetz, 2012). However, due to factors like uncertain energy prices and economic stagnation, the trajectory of CHP adoption relative to the 25% target has been unsatisfactory during the past few years. To examine the risk exposure of a hypothetical German microgrid with CHP and to study ways to mitigate it, we implemented a case study by estimating price parameters from the European Energy Exchange's (EEX) German electricity and gas spot markets, and Phelix and Natural Gas Futures markets from 2007-2012. While historical data for German electricity prices are available since 2002, the natural gas trading was launched only in 2007 (EEX Report, 2014), which, unfortunately, restricts our sample size significantly.

The electricity and gas price scenarios are constructed in two steps. First, we use the scenario tree method to generate average electricity ($\bar{P}^{\mathrm{e}}_{s_1^t}$) and gas ($\bar{P}^{\mathrm{g}}_{s_1^t}$) prices within every main period. Second, based on average prices within the main period, we generate scenario paths using the scenario fan method for electricity ($P^{\mathrm{e}}_{s_1^t,s_2,m}$) and gas ($P^{\mathrm{g}}_{s_1^t,s_2,m}$) spot prices for each subscenario and subperiod (Fig. 2.8). We solve the optimisation problem over a time horizon of eight years. Since a scenario tree-based problem combining two price processes scales exponentially with the number of decision stages, we limit the number of stages in the scenario tree to keep the problem computationally tractable. Using four main periods with two uncertainties gives us 64 ($2^{2(T-1)}$) different main scenarios and with 10 subscenarios for each node in the main scenario tree, this produces 640 different scenarios in total. Each main period covers two years, and since we have eight subperiods per a main period, a subperiod covers a quarter. We use yearly average electricity and gas prices to estimate the parameters for the scenario tree and quarterly average electricity and gas spot prices to estimate the parameters for the scenario fan (Table 2.1). Geometric Brownian motion is one of the most frequently used price processes in a discrete-time lattice-based model (Cox et al., 1979). While GBMs do not take into account important characteristics of commodity price dynamics (i.e., mean reversion or jumps in electricity price), these effects on modelling long-term average prices can be negligible (Pindyck, 1999). Consequently, GBM is used widely to model long-term electricity and gas prices (Fleten et al., 2007). To invoke GBM to model a price process, several assumptions must be met. The logarithm of ratios of consecutive prices need to be normally distributed with constant mean and variance and they have to be independent of their past values (Marathe and Ryan, 2005). To check the normality assumptions for quarterly average electricity prices (Fig. 2.9), we run the Shapiro-Wilk test (Sheskin, 2003), and to assess serial independence, we run the Breusch-Godfrey test (Johnston and DiNardo, 1997). Based on obtained p-values (Table 2.2), we cannot reject the hypotheses that quarterly average electricity and gas prices follow GBMs. On the other hand, we find significant correlation between quarterly electricity and gas prices ($p = 0.01$). Nevertheless, since our sample size is too small, these tests have low statistical power, and we cannot apply them with any reliability for yearly average prices. Still, our data support more the assumptions of correlated GBMs than that of other processes, i.e., mean-reversion, therefore, we assume that in our model both long-term and short-term price processes follow correlated GBMs. Regardless of the possible flaws associated with such a sample size, our aim is not to predict future prices but to generate feasible scenarios that reflect price uncertainties (Schumacher, 1993).

Table 2.1: Estimated Parameters for Electricity and Gas Prices

	Electricity	Gas
Starting price (€/MWh)	49.0	21.0
Yearly average spot price:		
Price volatility (σ_o^e,σ_o^g)	27.5%	22.5%
Price correlation (ρ_o)	0.80	
Quarter-yearly average spot price:		
Price volatility (σ_q^e,σ_q^g)	30.1%	18.9%
Price correlation (ρ_q)	0.83	
Two-yearly futures:		
Risk premium (R^e,R^g)	13%	3%



(a) Main Scenarios (b) Subscenarios

Figure 2.8: Scenario Generation

Table 2.2: Goodness of Fit

	Shapiro-Wilk Test	Breusch-Godfrey Test
Quarterly average electricity price	$p = 0.07$	$p = 0.58$
Quarterly average gas price	$p = 0.34$	$p = 0.31$

The scenario tree is generated through an extension of the log-transformed binomial lattice (Gamba and Trigeorgis, 2001). At end of each main period, the average electricity (gas) price can increase, $U^{\mathrm{e}}_{s_1^t} = +1$ ($U^{\mathrm{g}}_{s_1^t} = +1$), or decrease $U^{\mathrm{e}}_{s_1^t} = -1$ ($U^{\mathrm{g}}_{s_1^t} = -1$). Thus, from each node there are four branches, each corresponding to a different state of the average electricity and gas prices. The scenarios generated from the scenario tree are

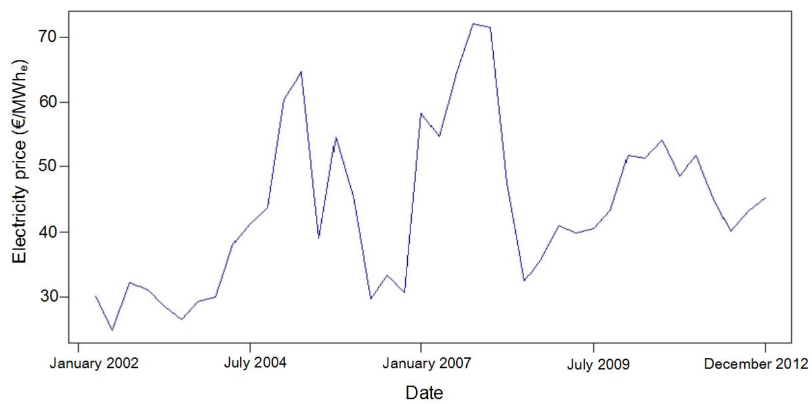


Figure 2.9: Quarterly Average Electricity Price

called main scenarios and are indexed by $s_1^t \in \mathcal{S}_1^t$. We assume that the long-term average gas and electricity prices follow GBMs with zero drift.

$$\ln \bar{P}^{\mathrm{e}}_{s_1^t} = \ln \bar{P}^{\mathrm{e}}_{s_1^{t-1}} + \sigma^{\mathrm{e}}_{\mathrm{o}} \sqrt{H_{\mathrm{o}}} U^{\mathrm{e}}_{s_1^t} \tag{2.15}$$

$$\ln \bar{P}^{\mathrm{g}}_{s_1^t} = \ln \bar{P}^{\mathrm{g}}_{s_1^{t-1}} + \sigma^{\mathrm{g}}_{\mathrm{o}} \sqrt{H_{\mathrm{o}}} U^{\mathrm{g}}_{s_1^t} \tag{2.16}$$

$$(U^{\mathrm{e}}_{s_1^t}, U^{\mathrm{g}}_{s_1^t}) = \begin{cases} (+1,+1) & \text{with probability } \frac{(1+\rho_{\mathrm{o}})}{4} \\ (+1,-1) & \text{with probability } \frac{(1-\rho_{\mathrm{o}})}{4} \\ (-1,+1) & \text{with probability } \frac{(1-\rho_{\mathrm{o}})}{4} \\ (-1,-1) & \text{with probability } \frac{(1+\rho_{\mathrm{o}})}{4} \end{cases} \tag{2.17}$$

Once we generate for each main period and main scenario the average electricity ($\bar{P}^{\mathrm{e}}_{s_1^t}$) and gas ($\bar{P}^{\mathrm{g}}_{s_1^t}$) prices, we generate scenario paths based on a scenario fan, which are referred to as subscenarios and indexed by $s_2 \in \mathcal{S}_2$. This way, we obtain the electricity ($P^{\mathrm{e}}_{s_1^t,s_2,m}$) and gas ($P^{\mathrm{g}}_{s_1^t,s_2,m}$) spot prices for each subscenario and subperiod based on the average price within the main scenario. Similarly as above, we assume that prices in subperiods follow correlated GBMs with zero drifts and are generated through the well-known stochastic differential equation of the correlated GBMs (Hull, 2012). In a discrete-time GBM with zero drift, the difference follows a Wiener process. Accordingly, in correlated GBMs, the corresponding Wiener processes are correlated:

$$P^{\mathrm{e}}_{s_1^t,s_2,m'} = \bar{P}^{\mathrm{e}}_{s_1^t} + \sum_{m=1}^{m'} \sigma^{\mathrm{e}}_{\mathrm{q}} \epsilon^{\mathrm{e}}_{s_1^t,s_2,m} \tag{2.18}$$

$$P^{\mathrm{g}}_{s_1^t,s_2,m'} = \bar{P}^{\mathrm{g}}_{s_1^t} + \sum_{m=1}^{m'} (\sigma^{\mathrm{g}}_{\mathrm{q}} \rho_{\mathrm{q}} \epsilon^{\mathrm{e}}_{s_1^t,s_2,m} + \sigma^{\mathrm{g}}_{\mathrm{q}} \sqrt{1-\rho^2_{\mathrm{q}}} \epsilon^{\mathrm{g}}_{s_1^t,s_2,m}) \tag{2.19}$$

where $\epsilon^{\mathrm{e}}_{s_1^t,s_2,m} \sim N(0,1)$ and $\epsilon^{\mathrm{g}}_{s_1^t,s_2,m} \sim N(0,1)$. Finally, the prices of electricity ($F^{\mathrm{e}}_{s_1^t}$) and gas ($F^{\mathrm{g}}_{s_1^t}$) futures contracts are calculated as the expected spot price in the main scenario s_1^t, where Q_{s_2} is the probability of subscenario s_2, multiplied by the risk premia (R^{e} for electricity futures and R^{g} for gas futures) representing the persistent differences between the futures prices and their expected spot prices (Kettunen et al., 2010), which are estimated using past futures prices and average spot prices (Table 2.1):

$$F^{\mathrm{e}}_{s_1^t} = \left(\sum_{s_2 \in \mathcal{S}_2} Q_{s_2} \frac{1}{M} \sum_{m=1}^{M} P^{\mathrm{e}}_{s_1^t, s_2, m} \right) (1 + R^{\mathrm{e}}) \tag{2.20}$$

$$F^{\mathrm{g}}_{s_1^t} = \left(\sum_{s_2 \in \mathcal{S}_2} Q_{s_2} \frac{1}{M} \sum_{m=1}^{M} P^{\mathrm{g}}_{s_1^t, s_2, m} \right) (1 + R^{\mathrm{g}}) \tag{2.21}$$

We illustrate the effect of physical and financial hedges on the decision-making process through several cases, which differ in terms of available hedges (Table 2.3). The microturbine parameters (Table 2.4) are collected from Siler-Evans et al. (2011), Giaccone and Canova (2009), and Galanti and Massardo (2011).

We consider microturbines, small-scale gas turbines with capacity size less than 1000 kW (Pipattanasomporn, 2005), without heat exchangers (MT) and microturbines with heat exchangers (MT-HX) with different capacity sizes. While an MT has lower total efficiency than an MT-HX, MTs cost less and have been commercially available over a longer period; therefore, they are often considered first for small-scale generation investment (McDonald, 2000; Zhu et al., 2002; Nascimento et al., 2008). Other parameters, including electricity and heat loads, the CO_2 tax, the risk-free interest rate, and the confidence level for the CVaR, are specified in Table 2.5. Note that the tax on CO_2 emissions and operational and maintenance costs remain constant in real terms over the entire time horizon. In each case, we examine different regimes in terms of the level of risk aversion (B). With these numerical examples, we examine whether on-site generation investments can be regarded as physical hedges to mitigate the microgrid's risk exposure and how they interact with financial hedges, such as electricity and gas futures. The optimisation problems are implemented in the General Algebraic Modeling System (GAMS) using the basic open-source nonlinear mixed integer programming (BONMIN) solver on a desktop with an Intel Core i7 2.79GHz CPU and 8GB RAM. The running times range from 40 to 280 minutes.

Table 2.3: Different Cases of Running the Microgrid

Case	Electricity futures	Gas futures	DER investment
1 - No hedges			
2 - Electricity futures only	X		
3 - Gas futures only		X	
4 - Both futures	X	X	
5 - Physical hedges			X
6 - Physical hedges with electricity futures	X		X
7 - Physical hedges with gas futures		X	X
8 - Physical hedges with both electricity and gas futures	X	X	X

Table 2.4: Available Technologies of Microturbines (MT) with and without Heat Exchanger (HX)

Technology index (i)	Type of generation unit	Capacity $\left(K_i^{\mathrm{e}}(kW_{\mathrm{e}})\right)$	Electrical conversion efficiency (E_i^{e})	Total efficiency of producing electricity and useful thermal energy ($E^{\mathrm{e}}+E^{\mathrm{e}}E^{\mathrm{h}}$)	Total investment cost (M€)
1	MT-small-1	200	30%	30%	0.20
2	MT-small-2	400	30%	30%	0.40
3	MT-medium	600	30%	30%	0.60
4	MT-HX-small-1	200	27%	78%	0.27
5	MT-HX-small-2	400	27%	78%	0.54
6	MT-HX-medium	600	35%	88%	0.77

Table 2.5: Microgrid Parameters and CO_2 Tax

Length of main period (H_{o})	2 a (17520 h)
Length of subperiod (H_{q})	0.25 a (2190 h)
Electricity demand (D^{e})	1 $\mathrm{MW_e}$
Heat demand (D^{h})	1.5 MW
CO_2 emissions tax (L^{c})	€21/ton
Operational and maintenance cost (V^{e})	€2/MWh
Risk-free annual interest rate (r)	1%
Confidence level for the CVaR (A)	95%

2.4.2 Overview of Insights

Our findings confirm that on-site generation with CHP reduces both expected energy costs and CO_2 emissions compared to cases with no on-site investment. In addition, the results indicate that on-site generation can hedge against volatile electricity prices, even if on-site generation has low efficiency or if the spread between electricity and gas prices decreases. Finally, we show that on-site generation as a physical hedge can be substituted with or complemented by financial hedges. The main results for a risk-neutral microgrid ($B = 0$) across different cases, with and without the possibility of CHP investment, are summarised in Table 2.6. Table 2.7 presents the same results for a maximally risk-averse ($B = \infty$) microgrid, i.e., with large values of B for which the CVaR reaches its minimum. Note that, due to no-arbitrage futures pricing, i.e., price of futures cannot be lower than expected spot prices for the corresponding period, futures purchases are always zero in the risk-neutral regime. Table 2.8 shows how a lower gas spark spread, the difference between the price of electricity and the cost of producing electricity using a central gas-fired power plant, affects the microgrid's investment decision. These results are obtained either by increasing the gas spot price by 20% and 50%, or by decreasing the electricity spot price by 16% and 33% compared to the original prices in each scenario.

Table 2.6: Results in a Risk-Neutral Regime ($B = 0$)

Case	Expected Cost (M€)	CVaR (M€)	Installed Capacity (kW_e)	Expected CO_2 emissions (kiloton)	Efficiency of the microgrid
Cases 1–4 and Cases 5–8 w/o CHP	7.59	12.83	0	59.19	72.2%
Cases 5–8 w/ CHP	7.02	10.69	800	49.14	79.0%

Insight 1: CHP microturbines reduce the expected cost compared to purchasing electricity from the market or generating electricity without heat recovery.

From Table 2.6, the installation of CHP in Cases 5–8-w/ CHP leads to a significant decrease in expected cost compared to Cases 1–4 and Cases 5–8-w/o CHP. Over the eight-year period, the reduction in expected cost with CHP is €0.58M. Furthermore, compared to Cases 1–4, the overall efficiency of the microgrid increases in Cases 5–8-w/ CHP. Note that the benchmark for efficiency is relatively high, as significant proportions of Germany's electricity are generated using nuclear power and renewable energy sources, 15.4% and 24.1%, respectively [2]. Nevertheless, this modest increase in efficiency in Cases 5–8-w/ CHP translates into a significant decrease in CO_2 emissions over the eight-year period. It is equivalent to a 2.3% annual rate of decline over the same period, which is significantly larger than the 0.5% annual decrease recorded over the last eight-year period in Germany. This result provides support for German CHP laws, which aim to promote

[2] Statistisches Bundesamt. Available: https://www.destatis.de/DE/ZahlenFakten/ImFokus/Energie/Kernenergie.html

CHP installation in order to reach the 2020 targets.

Insight 2: On-site generation reduces the microgrid's risk exposure compared to purchasing electricity from the spot market.
The CVaR of the microgrid can be diminished by decreasing either its expected cost or the volatility of its running cost. The microgrid's CVaR is the highest when it meets all of its electricity demand by purchasing from the spot market and uses the boiler for heating, also purchasing all of its gas from the spot market. When CHP is installed in Case 5-w/ CHP, both under risk-neutral and risk-averse regimes (see Tables 2.6 and 2.7), the microgrid's CVaR decreases by €2.14M compared to Case 1. As the difference between the expected cost in Case 5-w/ CHP and Case 1 is €0.58M, the remaining part of the CVaR reduction, €1.57M, is due only to the lower volatility of the cost of running the microgrid. Thus, the majority of the reduction in the CVaR arises from swapping electricity spot purchases for gas spot purchases using CHP. The CVaR is reduced the same way in Cases 5–8-w/o CHP, but the microgrid invests in on-site generation only under risk-averse regimes. Since the MT w/o HX has low efficiency, it cannot reduce the expected cost; however, it still can reduce the microgrid's CVaR by using gas spot with low volatility when the electricity price peaks.

Table 2.7: Results in a Risk-Averse Regime ($B = \infty$)

Case	Expected Cost (M€)	CVaR (M€)	Installed Capacity (kW_e)	Electricity futures[a]	Gas futures for boiler [b]	Gas futures for MT [c]	Expected CO_2 emissions (kt)	Efficiency of the microgrid
1	7.59	12.83	0	0%	0%	0%	59.19	72.2%
2	7.70	12.02	0	9.0%	0%	0%	59.19	72.2%
3	7.62	12.63	0	0%	10.7%	0%	59.19	72.2%
4	7.69	11.97	0	7.0%	3.8%	0%	59.19	72.2%
5-w/ CHP	7.02	10.69	800	0%	0%	0%	49.14	79.0%
6-w/ CHP	7.03	10.63	800	1.1%	0%	0%	49.14	79.0%
7-w/ CHP	7.06	10.48	800	0%	1.7%	3.0%	48.96	79.2%
8-w/ CHP	7.07	10.44	800	0.7%	1.6%	3.1%	48.96	79.2%
5-w/o CHP	7.88	12.30	800	0%	0%	0%	60.86	68.1%
6-w/o CHP	7.80	11.96	400	6.7%	0%	0%	60.02	70.0%
7-w/o CHP	7.91	12.06	800	0%	8.2%	0.4%	60.87	68.0%
8-w/o CHP	8.10	11.82	600	5.6%	9.2%	0.7%	61.20	68.3%

[a] Fraction of electricity consumption supplied from electricity futures
[b] Fraction of heat consumption from boiler supplied from gas futures
[c] Fraction of electricity consumption supplied from gas futures

Insight 3: CHP facilitates risk management even when the expected gas spark spread is negative.

When the difference between electricity and gas spot prices diminishes substantially and the gas spark spread becomes negative, most gas-fired power plants stop operating. As CHP is more efficient than large power plants, a risk-neutral microgrid in Case 5-w/ CHP invests in on-site generation if the negative expected gas spark spread is the result of increasing gas prices (see Table 2.8). However, if the negative gas spark spread is due to low electricity prices, then continuous on-site generation with CHP also becomes uneconomical, and a risk-neutral microgrid is better off with purchasing all electricity from the spot market. Nevertheless, a risk-averse microgrid still invests in a CHP unit as it can hedge against electricity price volatility and decreases the microgrid's CVaR (see Table 2.8). These findings indicate that on-site generation, as a physical hedge, represents additional value for risk-averse consumers, since, similarly to swaptions (Hull, 2012), it gives the microgrid an option to swap electricity price for gas prices. Thus, even under a decreasing expected spark spread, on-site generation with CHP is an efficient risk management tool for consumers exposed to volatile electricity prices.

Table 2.8: Installed On-Site Generation in Case-5-w/ CHP for Different Spark Spreads

	Average ratio of electricity and gas spot prices[a]	Gas spark spread[b] (€/MWh)	Installed capacity at $B=0$ (kW_e)	Installed capacity at $B=1$ (kW_e)
Original prices	3.0	11.46	800	800
Increasing gas prices	2.5	2.1	800	800
	2.0	-13.3	600	600
Decreasing electricity prices	2.5	2.2	600	600
	2.0	-8.3	0	600

[a] Average ratio of electricity and gas spot prices $= \sum_{s_1^T \in \mathcal{S}_1^T} Q_{s_1^T} \sum_{s_2 \in \mathcal{S}_2} Q_{s_2} \frac{1}{TM} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} (\frac{P^{e}_{s_1^t, s_2, m}}{P^{g}_{s_1^t, s_2, m}})$

[b] Spark spread $= \sum_{s_1^T \in \mathcal{S}_1^T} Q_{s_1^T} \sum_{s_2 \in \mathcal{S}_2} Q_{s_2} \frac{1}{TM} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} (P^{e}_{s_1^t, s_2, m} - \frac{P^{g}_{s_1^t, s_2, m}}{E^{e}})$

where E^{e}=50.00% by convention (CDC Climate Research - Methodology, 2013)

Insight 4: Electricity futures and on-site generation are substitutes.

As consumers also have the possibility to hedge against price risk via the financial markets, it is important to assess how the availability of electricity futures affects the microgrid's investment decisions in on-site generation. Comparing the cases with risk-averse regimes, Case 2 and Case 6-w/ CHP in Table 2.7, the proportion of electricity futures purchased decreases significantly when CHP is present. Since CHP generation is very efficient, it can decrease CVaR at a lower cost by producing energy on-site whenever the spot electricity price peaks. Therefore, electricity futures have less scope for CVaR reduction and are used very rarely. On the other hand, when only the less efficient MT without HX can be installed, the availability of electricity futures decreases the need for on-site generation. This is why the installed capacity drops to 400 kW_e in Case 6-w/o CHP compared to 800 kW_e in Case 5-w/o CHP. Consequently, these findings show that electricity futures and on-site generation are substitutes.

Insight 5: Gas futures and on-site generation are complements.
The microgrid can purchase gas futures for on-site generation or for the boiler. Since the gas spot price has low volatility, gas futures for the boiler can reduce the CVaR only slightly. Nevertheless, as the boiler is more efficient than MT w/o HX, these purchases assist on-site investment in Case 8-w/o CHP, where the installed capacity is 200 kW_e higher compared to Case 7-w/o CHP, when only electricity futures are available (see Table 2.7). Gas futures for on-site generation would increase the running cost of the microgrid in Case 8-w/o CHP; however, the microgrid can mitigate some of the price volatility of spot gas for the MT by purchasing gas futures for the more efficient boiler. On the other hand, when CHP is installed, the microgrid purchases most of the gas futures for the MT, thereby further reducing the microgrid's exposure to electricity price volatility. While the share of gas futures in electricity generation is still relatively small, i.e., 3.0% and 3.1% in Cases 7 and 8-w/ CHP, respectively, they contribute significantly to the CVaR reduction of the microgrid. For example, in Case 7-w/ CHP, if the microgrid could not use gas futures for MT, then the CVaR would increase by €0.11M. Therefore, while the combined share of gas futures purchases for the MT and for the boiler are the lowest in Cases w/ CHP, gas futures become more cost-effective in reducing CVaR when CHP is present.

Summary
According to the European Cogeneration Review (2013), the biggest obstacles to CHP adoption in Germany are risk aversion and an unfavourable gas spark spread. This is why it is important to note that, in fact, on-site generation can work as a physical hedge by reducing the consumers' CVaR, which is not captured by NPV and real options analyses. Under a positive gas spark spread, even cheaper but less-efficient technologies, i.e., microturbines without heat exchangers, can limit risk exposure to peaking electricity prices. Furthermore, conforming to the results of Maribu and Fleten (2008), we find that consumers can decrease their expected cost by investing in CHP, which can also function as an efficient hedge in case of a significant reduction in the average gas spark spread. However, a liquid electricity futures market might have an adverse effect on on-site generation.

Indeed, the availability of electricity futures can decrease the willingness of risk-averse consumers to invest in technologies w/o CHP since they can be as effective in reducing CVaR as on-site generation without heat recovery. By contrast, the availability of gas futures can contribute to more investment in on-site generation, as shown in Cases 7-w/ and w/o CHP. While financial hedges play an important role in risk management, from a social point of view, CHP investments provide more benefits in terms of lower CO_2 emissions and more reliable electricity supply. Thus, policies affecting electricity and gas markets can also influence progress towards the 2020 CHP goals in Germany. To examine how the interaction between physical and financial hedges affect on-site generation investment, we investigate each type of hedge separately and perform sensitivity analyses in terms of electricity price volatility as well as and electricity and gas price correlation.

2.4.3 Insights without On-Site Generation

In order to understand better the interaction between financial and physical hedges, we first examine the effectiveness of financial hedging alone. To do so, we focus on the efficient frontier for Cases 1–4. Such frontiers are delimited by varying the B parameter in order to make determinations about the mean-risk tradeoff. The rate of tradeoff can be analysed through comparing the slope of the mean-risk efficient frontier, from which we can derive the amount of CVaR reduction per €1 increase in the expected cost. Fig. 2.10 shows the efficient frontier for Cases 1–4. The largest decrease in CVaR is between $B = 0$ and $B = 0.35$. At this level of risk aversion, gas futures are more efficient than electricity futures at reducing CVaR, i.e., a €1 increase in expected cost with gas futures leads to larger CVaR reduction, but the effect of electricity futures is larger, i.e., they reduce the CVaR by €0.78M compared to €0.19M with gas futures. This is because the electricity spot price is more volatile than the gas spot price, which means that electricity futures can reduce CVaR to a larger extent, even though their risk premium is higher (Table 2.1). Hence, a microgrid with only financial hedges can reduce its CVaR mostly by purchasing electricity futures.

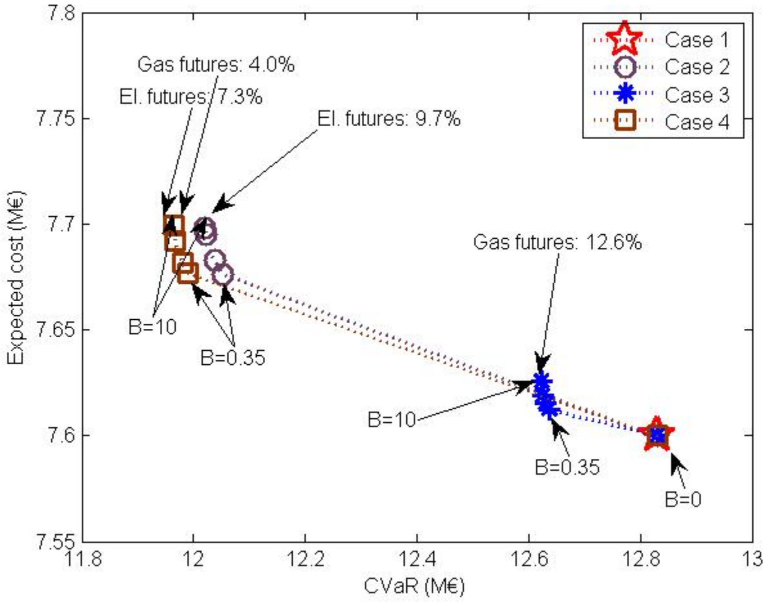


Figure 2.10: Efficient Frontiers for Cases 1–4

2.4.4 Insights with MT without Heat Recovery

To further elaborate on the main insights, we also examine the mean-risk tradeoff of cases without CHP. Compared to the financial hedges in Cases 2–4, MT w/o HX on its own is less effective. The maximum CVaR reduction in Case 5-w/o CHP is 4%, compared to 7% with financial hedges, and it is reached at a much higher cost. The reason for this is that the MT w/o HX has a low electrical conversion rate, which can be used only in a few scenarios, but its capital cost increases the microgrid's expenditure in each scenario. Conversely, the microgrid can decide in every main period whether to enter into futures contracts, which makes financial hedges less burdensome on the expected cost.

Insight 2-w/o CHP: Less efficient on-site generation can also reduce the microgrid's risk exposure.

From the results presented in Tables 2.6 and 2.7, we conclude that microturbines without heat exchangers are always inferior to CHP, but they still can function as a physical hedge. In the risk-neutral regime ($B = 0$), the microgrid does not install any on-site generation in cases w/o CHP. Nevertheless, in risk-averse regimes ($B > 0$), the microgrid installs microturbines whenever they are available. Furthermore, the more risk averse the microgrid becomes, the more generation capacity it installs (Fig. 2.11). As above, the reason for this is that the volatility of the gas spot price is lower than that of the electricity spot price. The microgrid can, therefore, decrease its CVaR by installing on-site generation and swapping the volatile electricity spot price for the less volatile gas spot price. For example, in Case 5-w/o CHP at $B = 0.37$, the microgrid invests in 200 kW_e of on-site generation (Fig. 2.12). Due to its low efficiency, the microturbine supplies only 3.6% of the electricity load but has the potential to supply 20%. Thus, even though the microturbine lies mostly idle, it still enables the microgrid to avoid peaking electricity prices, thereby significantly decreasing its CVaR.

Insight 4-w/o CHP: The degree of the substitution effect between electricity futures and on-site generation is determined by the level of risk aversion. Figs. 2.11 and 2.12 show that the microgrid invests in less on-site generation capacity when electricity futures are available. This indicates that electricity futures and on-site generation are substitutes in the sense that increasing the purchases of electricity futures reduces the scope of on-site generation for CVaR reduction. Conversely, lowering the risk premium for electricity futures (decreasing the investment cost of MT) reduces the risk-averse demand for on-site generation (electricity futures). However, this substitution effect is asymmetric with the cross-price elasticity depending on the level of risk aversion. At $B = 100$, a one percentage point decrease in the risk premium for electricity futures leads to lower on-site generation investment. On the other hand, at the same level of risk-aversion, only a 20% decrease in the investment cost would result in more on-site generation investment and less futures purchases. At a lower level of risk aversion, $B = 1$, when the microgrid installs the 200 kW_e MT, a 14% decrease in the price of MT is sufficient to increase the demand for on-site generation to 400 kW_e, while only a 12% decrease in the risk premium would result in no on-site investment and increased electricity futures purchases. The substitution effect between electricity futures and on-site generation is asymmetric because their effects on CVaR reduction are also asymmetric. Investing in on-site generation gives the option to the microgrid to swap gas spot prices for electricity prices. With on-site generation with low efficiency, the spread between gas and electricity spot prices has to be sufficiently large so that the CVaR reduction from on-site generation remains larger than the increase in the expected cost. As such a high price spread occurs infrequently, the 400 kW_e MT remains idle predominantly, while the 200 kW_e MT is sufficient most of the time. This is why the substitution effect of electricity futures is larger when the 400 kW_e MT is installed. Thus, in terms of CVaR reduction, MT w/o HX is the most competitive against financial futures if installed in small capacity.

Insight 5-w/o CHP: The complementary effect between gas futures and on-site investment depends on the level of risk aversion. At $B = 100$ in Case 8-w/o CHP, a two percentage point decrease in the risk premium for gas futures increases the demand for on-site generation from 600 kW_e to 800 kW_e. At the same level of risk aversion, a 10% decrease in the investment cost increases the on-site investment to 800 kW_e and, hence, increases the demand for gas futures for boiler from 5.1% to 6.9% of the heat demand. Thus, gas futures have a larger impact when the marginal CVaR reduction of on-site investment is small, which in Case 8-w/o is also due to the presence of electricity futures, which are substitutes to on-site generation. This is why in Case 7-w/o CHP, when electricity futures are not available, the marginal effect of on-site generation on CVaR reduction increases and the role of gas futures becomes more limited. At the risk-aversion levels specified on Fig. 2.11, a decrease in the risk premium for gas futures does not lead to more investment. On the other hand, a decrease in the investment cost leads to more investment, which in turn leads to more gas futures purchases. Therefore, in Case 7-w/o CHP, on-site generation is a better complement as it has a stronger effect on gas futures purchases than gas futures purchases have on the investment decision. Nevertheless, the presence of gas futures still affects the investment decision, as indicated by the mean-risk efficient frontiers of Cases 5 and 7-w/o CHP. When gas futures are present, in Case 7-w/o CHP, investment decisions are triggered at lower B compared to Case 5. For example, the microgrid invests in 400 kW_e at $B = 0.35$ when gas futures are available and at $B = 0.50$ when gas futures cannot be purchased.

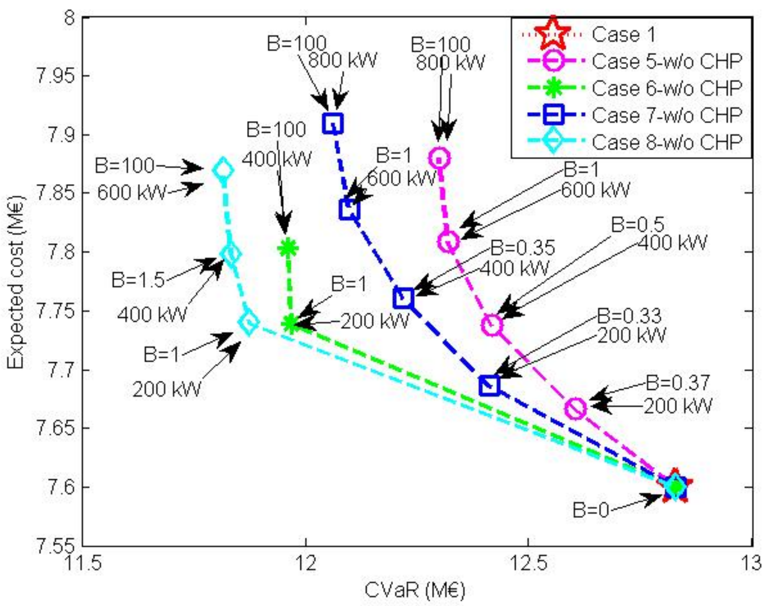


Figure 2.11: Efficient Frontiers for Cases 5–8 w/o CHP with Installed Capacity Indicated

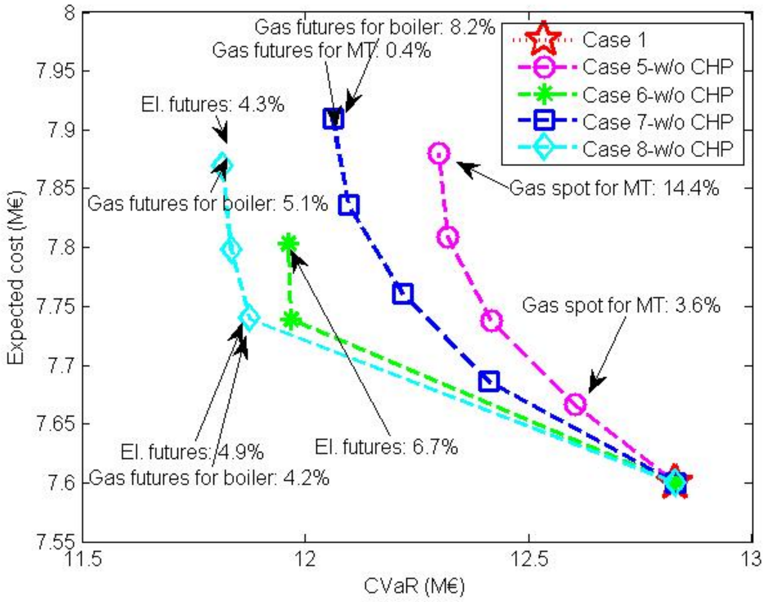


Figure 2.12: Efficient Frontiers for Cases 5–8 w/o CHP with Spot and Futures Purchases Indicated

2.4.5 Insights with CHP

Having demonstrated the effectiveness of CHP in decreasing the microgrid's expected cost, we now further examine Cases 5–8-w/ CHP by focusing on the CHP's role in risk management. As shown in Fig. 2.13, Cases 5–8-w/ CHP have much lower expected cost and CVaR than Case 1. Furthermore, the installed generation capacity is the same in all risk-neutral and risk-averse regimes. As the CHP is efficient, the microgrid uses on-site generation to decrease its expected cost in the risk-neutral regime whenever the electricity price peaks. Thus, there is no scope for further CVaR reduction by swapping electricity for gas and, hence, the microgrid does not install more capacity in risk-averse regimes.

Insight 4-w/ CHP: The substitution effect of electricity futures for on-site generation is much weaker with CHP in comparison with MT w/o HX.

While the shares of both electricity and gas futures are lower compared to Cases 5–8-w/o CHP, the decrease in the use of electricity futures is larger than that of gas futures (see Case 8-w/ CHP in Fig. 2.14 and Case 8-w/o CHP in Fig. 2.12). When the installed generation capacity cannot be used economically, the electricity spot price is low with low volatility; therefore, the microgrid purchases electricity futures at only those main scenario nodes when the average gas spot price is relatively high and the electricity spot price is still volatile. As this happens rarely, the share of electricity futures is much lower than in cases w/o CHP. This indicates that MT w/ HX and electricity futures are substitutes. Since the microgrid invests in CHP in the risk-neutral regime, the substitution effect between on-site generation and electricity futures is much smaller for the risk-averse microgrid. In Case 6-w/ CHP at $B = 100$, only a 9 % decrease in the risk premium for electricity futures leads to 200 kW_e less on-site investment. In the same case, the investment cost of MTs w/ HX needs to increase by 40% to trigger additional electricity futures purchases. As the share of electricity purchases is low, increased risk premiums for electricity futures cannot affect the investment decision. Thus, investment in CHP is relatively insensitive to large changes in the electricity futures market.

Insight 5-w/ CHP: Gas futures for the boiler are substitutes, while gas futures for MT are complements for CHP investment.
The effect of gas futures on the use of on-site generation is somewhat ambiguous. On the one hand, the use of on-site generation increases the value of gas futures for MT; thus, gas futures and on-site generation are complements. On the other hand, gas futures might decrease the risk-averse demand for CHP as they can reduce the CVaR when used with the boiler. While in cases w/o CHP the boiler was operated independently of the MT, in cases w/ CHP, the microgrid does not run the boiler and the CHP at full capacity at the same time as this would generate heat waste. This is why gas futures for boiler and on-site generation with CHP can be substitutes. In Case 7-w/ CHP at $B = 100$, a change in the risk premium for gas futures does not affect the investment decision. However, when the investment cost increases, the demand for gas futures for MT decreases, while the demand for gas futures for boiler increases. The same interaction can be observed when we run Case 8-w/ CHP but without gas futures for MT. In the most risk-averse regime, the microgrid decreases its investment to 600 kW_e and increases its electricity futures and gas futures for boiler purchases. Comparing the effects of electricity and gas futures, in Case 8-w/ CHP, a 9% in the risk premium of electricity futures results in a 200 kW_e decrease in on-site investment. However, if this is accompanied by a 1% decrease in the premium of gas futures, then the microgrid maintains its 800 kW_e investment. Thus, gas futures and on-site generation are complements as the substitution effect of gas futures for the boiler is dominated by the complementary effect of gas futures for MT in most cases. The substitution effect of gas futures eclipses the complementary effect only when the economics of CHP deteriorate significantly. For example, in Case 8-w/ CHP at $B = 100$, if the cost of CHP increases by 40%, then the microgrid invests in less on-site generation; however, if gas futures for the boiler were not available, then it would still invest in 800 kW_e CHP. Thus, the availability of gas futures results in more investment in CHP under current market conditions.

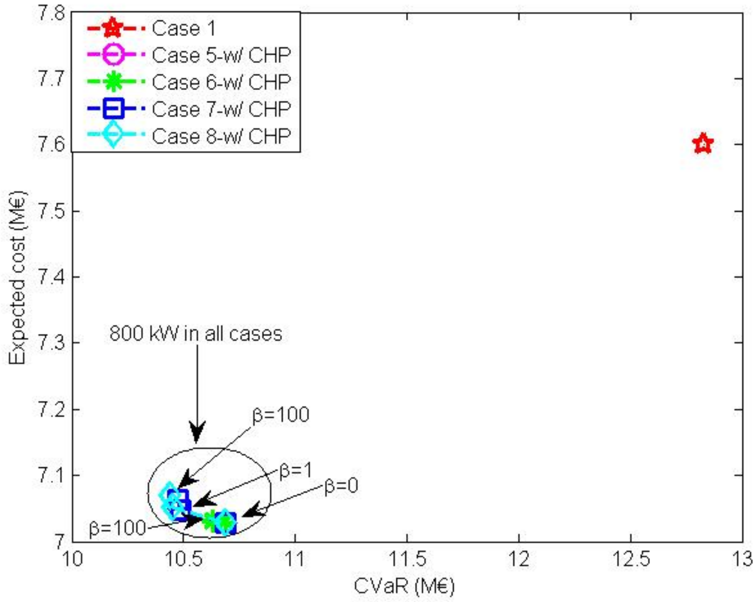


Figure 2.13: Efficient Frontiers for Cases 5–8 w/ CHP with Installed Capacity Indicated

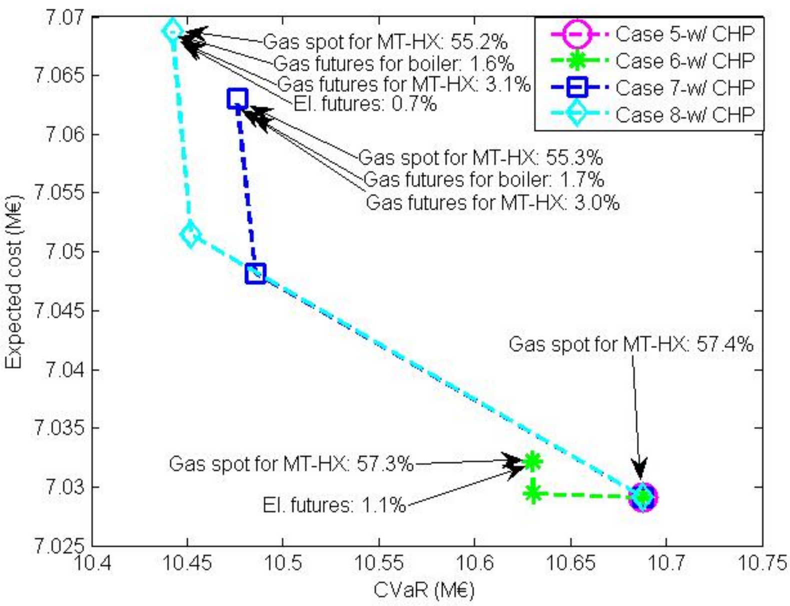


Figure 2.14: Efficient Frontiers for Cases 5–8 w/ CHP with Spot and Futures Purchases with $B = 0$, $B = 1$, and $B = 100$

2.4.6 Sensitivity Analysis

The increasing share of renewable generation has had a profound effect on the German energy markets. Ketterer (2014) shows that intermittent generation increases the wholesale electricity price. Furthermore, Paraschiv et al. (2014) find that the sensitivity of electricity price to gas price decreases over time due to the promotion of renewable energies. As these trends are expected to continue, we carry out sensitivity analyses in terms of increased electricity price volatility as well as gas and electricity price correlation. First, we run the optimisation problem with long-term ($\sigma_{\mathrm{Y}}^{\mathrm{e}}$) and short-term ($\sigma_{\mathrm{Q}}^{\mathrm{e}}$) electricity price volatility increased by 10%. Second, we run the optimisation problem with the long- and short-term correlation of electricity and gas prices halved, i.e., lowering them from $\rho_{\mathrm{Y}} = 0.80$ and $\rho_{\mathrm{Q}} = 0.83$ to $\rho_{\mathrm{Y}} = 0.40$ and $\rho_{\mathrm{Q}} = 0.42$, respectively.

Insight 6: With higher electricity price volatility, the value of on-site generation as physical hedges increases compared to financial hedges.

Fig. 2.16 illustrates the efficient frontiers for Cases 5–8-w/o CHP. In all cases, the microgrid invests in 1000 $\mathrm{kW_e}$ on-site generation in the risk-neutral regime, compared to no investment with the original electricity price volatility (Fig. 2.11). Again, the average share of on-site electricity generation is small (less than 25%). However, when the electricity price peaks, the microturbine works at full capacity. This way, the microgrid can decrease its expected cost and CVaR by 3% and 9%, respectively, compared to Cases 1–4 in the risk-neutral regime. This is larger than the CVaR reduction produced by the combined use of electricity and gas futures in Case 4 (Fig. 2.15). Even with volatile spot prices, the CVaR-reducing potential of financial hedges diminishes whenever spot prices exhibit large drops. This, however, does not affect negatively the capacity investment decisions, as the microgrid can purchase electricity from the spot market if prices decrease, while using on-site generation to hedge against price jumps.

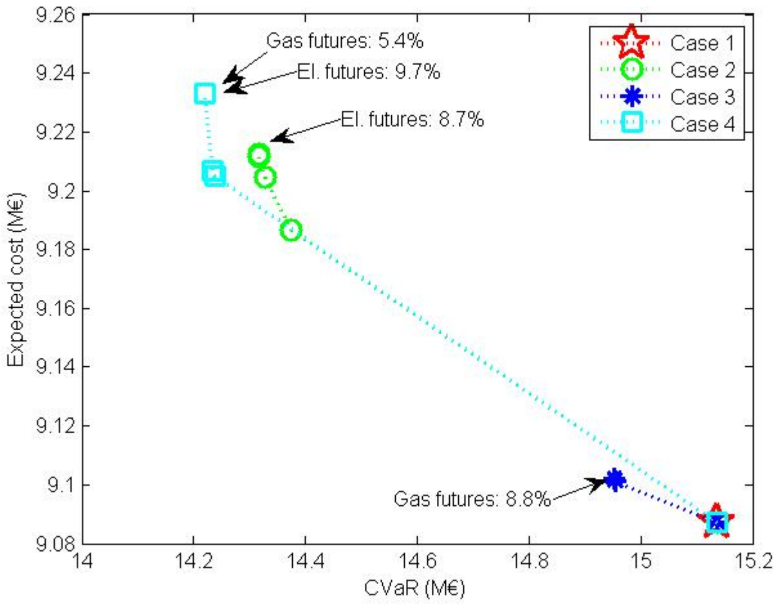


Figure 2.15: Efficient Frontiers for Cases 1–4 with $B = 0$, $B = 0.35$, $B = 1$, and $B = 10$ for Increased Electricity Price Volatility

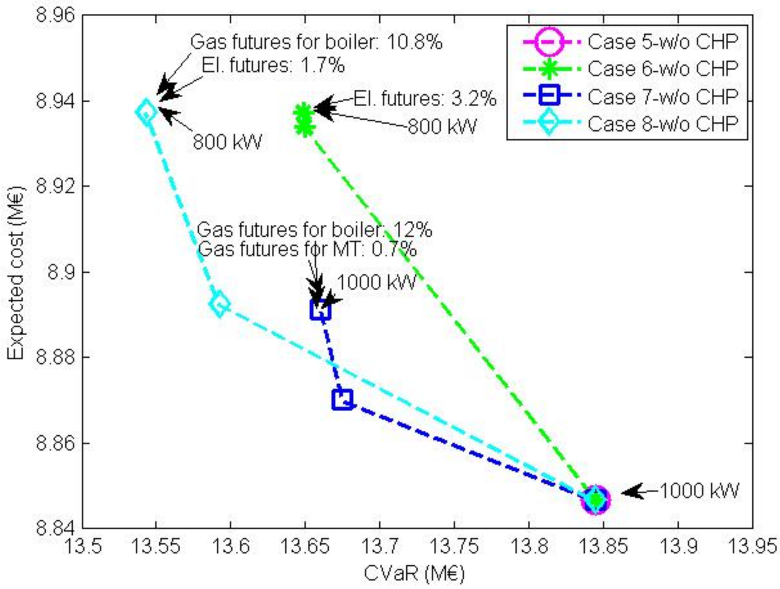


Figure 2.16: Efficient Frontiers for Cases 5–8 w/o CHP with $B = 0$, $B = 0.35$, $B = 1$, and $B = 10$ for Increased Electricity Price Volatility

The CVaR reduction of the microgrid is even larger with CHP (Fig. 2.17). The microgrid invests in 1000 kW_e capacity in risk-neutral regimes in Cases 5–8 w/ CHP and in risk-averse regimes in Cases 6–8. Investing in 1000 kW_e capacity means that, in some cases, the microgrid generates more heat from heat recovery than it requires. However, as the gap between electricity and gas spot price volatilities widens, the value of the option to swap electricity at a higher spot price for gas at a lower price substantially increases.

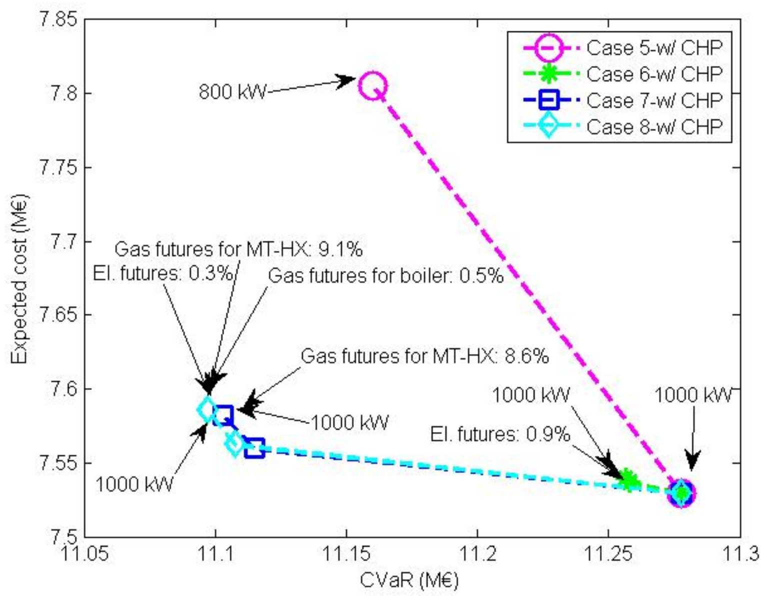


Figure 2.17: Efficient Frontiers for Cases 5–8 w/ CHP with $B = 0$, $B = 1$, and $B = 10$ for Increased Electricity Price Volatility

Insight 7: Under lower levels of electricity and gas price correlations, on-site generation works less efficiently as a physical hedge, but the complementary effect of gas futures increases.

In Cases 5, 6, and 8-w/ CHP, the risk-averse microgrid decreases the installed capacity to 800 kW$_e$ from the risk-neutral investment level of 1000 kW$_e$ (Fig. 2.18). In the risk-neutral regime, compared to the same cases with the original correlation rates, the microgrid requires a higher installed capacity in order to generate more electricity when the price difference is sufficient to recover the investment cost. However, a more risk-averse microgrid installs less capacity, as in scenarios with high gas prices and low electricity prices the microgrid cannot operate its CHP. In Case 7-w/ CHP, when gas futures are available, the risk-averse microgrid does not need to decrease its investment at $B = 1$ because it can use gas futures to hedge against uncorrelated volatile gas spot prices. However, in the most risk-averse regime ($B = 10$), even the presence of gas futures is not enough to maintain a higher investment level. Nevertheless, if the risk premium for gas futures decreases by 1%, then even in the most risk-averse regime the microgrid maintains its 1000 kW$_e$ capacity investment. This again indicates that gas futures and on-site generation interact complementarily. In this case, the complementary effect of gas futures is larger compared to the cases with original correlation or increased price volatility, when CHP can reduce the CVaR significantly on its own.

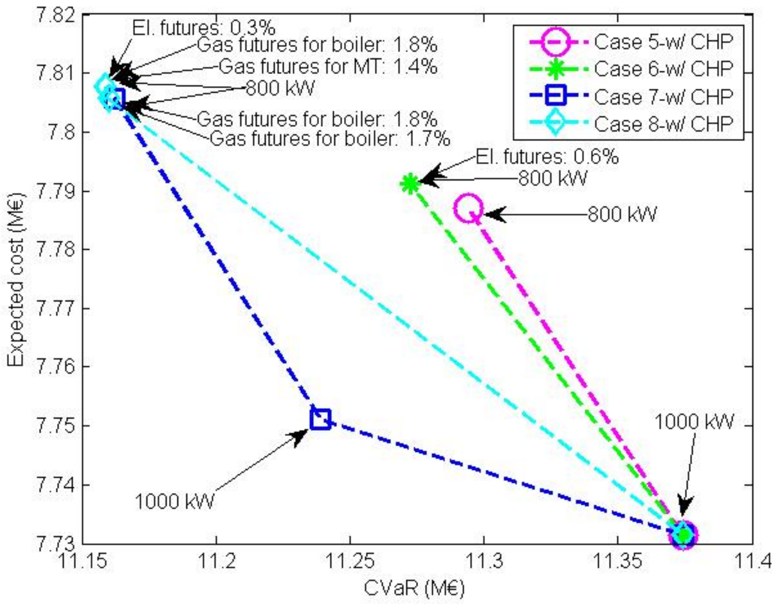


Figure 2.18: Efficient Frontiers for Cases 5–8 w/ CHP with $B = 0$, $B = 0.35$, $B = 1$, and $B = 10$ for Decreased Correlation of Electricity and Gas Spot Prices

2.5 Conclusions

Deregulation has introduced new challenges and opportunities within the energy sector. On the one hand, consumers face uncertain electricity and gas prices, which significantly increases their risk exposure. On the other hand, consumers can now invest in on-site generation or use futures to hedge against increased price risk. While financial hedges play an increasingly important role in the energy markets, investment in new technologies provides more social benefits, such as higher energy efficiency and lower CO_2 emissions, as shown in Siddiqui et al. (2005). Still, despite the ongoing efforts of policymakers in Germany to support CHP implementation (Kraft-Wärme-Kopplungs-Gesetz, 2002, 2008, 2012), the investment rate is lagging behind the desired targets.

Possible explanations for this are volatile gas spark spreads and risk aversion among smaller potential investors. Indeed, managing the risk from such ventures requires more sophisticated decision support. Using stochastic programming, we show that even if the gas spark spread decreases or the correlation between gas and electricity prices deteriorates in Germany, then on-site generation still remains an effective physical hedge against electricity price volatility, which is likely to increase due to the rising share of intermittent generation. Since conventional decision-making frameworks do not take into account risk aversion, decision makers using these techniques might overlook the significant value of CHP as physical hedge. As CHP is more energy efficient than purchasing electricity from the grid and using a gas-fired boiler for heat production, it is also associated with lower CO_2 emissions and can help to achieve the 2020 goals set by the EU. The microgrid's CVaR can be further decreased by combining on-site generation with electricity and gas futures. While we demonstrate that electricity futures and on-site generation are substitutes, the availability of electricity futures impede investments mostly in technologies without CHP. Microturbines with heat recovery are more efficient hedges as they can swap the high volatility of the electricity price for the low volatility of the gas spot price. Consequently, the microgrid is not exposed to peaks in electricity price when the use of financial futures would be a more costly alternative.

Intriguingly, we show that gas futures and on-site generation can complement each other, as a microgrid is more likely to install additional generation capacity when gas futures are available. In fact, the availability of gas futures can neutralise the substitution effect of electricity futures, thereby contributing to higher investment. Nevertheless, the interaction between financial and physical hedges depends on both the level of risk aversion of the microgrid and on the behavior of the underlying electricity and gas prices. Under increased electricity price volatility, on-site generation becomes more attractive, and even the installation of a less efficient microturbine without heat recovery can reduce expected cost. In contrast, when the correlation between electricity and gas spot prices is halved, on-site generation works less efficiently as a physical hedge on its own and the complementary effect of gas futures increases.

Chapter 3

Optimal Operation of Combined Heat and Power under Uncertainty and Risk Aversion

3.1 Introduction

Apart from the investment decision, large consumers need to consider also their medium-term operational risk management problem. In deregulated electricity industries, a consumer has the opportunity to meet its electricity and gas demand by purchasing from the spot and futures markets or through on-site generation. Recently, trade in both medium-term gas and electricity futures has increased (EEX Press Release, 2014) and now the potential consumers can choose from different futures contracts in terms of load profile and the length of the contract. While purchasing futures contracts can reduce the risk associated with the volatility of spot prices, it can also mean higher operational costs because of risk premia of futures contracts. Another option is on-site generation, which requires more sophisticated decision support and is exposed to the gas price volatility. Similarly, consumers relying on purchases from wholesale electricity markets can benefit from large price drops in countries with high share of intermittent generation but are exposed to increasing price volatility (Woo et al., 2011). Thus, there are a lot of tradeoffs to consider that may not be evaluated adequately via conventional deterministic models.

Addressing this problem can encourage on-site investment, which in turn can lead to lower CO_2 emissions compared to purchasing electricity from the main grid (Siddiqui et al., 2005). For the aforementioned reasons, Germany has adopted three CHP laws to support investment into small- and large-scale CHP (Kraft-Wärme-Kopplungs-Gesetz, 2002, 2008, 2012). However, the targets regarding the higher share of cogeneration have not yet been achieved (Streckiene et al., 2009).

Some of the possible reasons for lower than expected investment in CHP are the electricity and gas price uncertainties in deregulated industries (European Cogeneration Review - Germany, 2013). Koller et al. (2012) argue that middle level-managers show strong bias against risk as a result of flawed reward systems within companies. They find that lead managers are often unwilling to tolerate uncertainty even when a project's potential earnings far outweigh its potential losses.

In order to examine the risk that large consumers face, we formulate a multi-stage, mean-risk optimisation model for the medium-term operational risk management of a microgrid with installed CHP. Our objective is to gain insights into managing risk in a microgrid over a one-month period using futures contracts and on-site generation. We assume uncertain electricity and gas spot prices and the availability of monthly and weekly electricity futures and monthly gas futures. The microgrid needs to meet its electricity demand by either purchasing electricity from the markets or through on-site generation. In addition, the microgrid needs to satisfy its heat loads by using either a boiler or heat recovery. Thus, compared to the previous chapter which considered quarterly average spot prices and yearly futures contracts, we provide a more realistic description of operational hedging strategies for a large consumer. We find that the use of CHP not only lowers the microgrid's expected running cost significantly but also reduces its risk exposure compared to on-site generation without heat recovery or to purchasing all electricity from the main grid. We also find that the availability of monthly gas futures increases on-site generation with CHP, thus indicating that CHP and gas futures are complements.

3.2 Literature Review

Research interest in consumer energy procurement has steadily grown over the last two decades. Studies with deterministic models demonstrate that consumers participating in the electricity market can reduce their costs significantly. Through a case study, Talati and Bednarz (1998) present different methodologies for large industrial customers to manage their electricity purchases in a competitive power industry. They suggest that future regulatory changes are likely to trigger higher electricity pool prices, which might justify investments in cogeneration. Kirschen (2003) considers some aspects of the electricity market from the perspective of a large consumer. Specifically, he points out that electricity markets could benefit consumers, but this requires adoption of more sophisticated decision support. In this vein, Conejo et al. (2005) consider a large consumer that procures its electricity demand from both pool and bilateral transactions, or through operating a self-production unit. They provide a procedure that, provided all the required information is available, allows a large consumer to decide optimally its mix of purchases from different electricity sources. Siddiqui et al. (2005) compare the economic benefit of installing different types of DG (reciprocating engines with or without heat recovery and photovoltaic panels) at a hypothetical microgrid that supplies heat, cooling, and electricity to a commercial building using the DER-CAM. Using mixed-integer linear programming (MILP), they find that investing in gas-fired CHP turbines leads to the lowest energy cost and also reduces CO_2 emissions.

Studies incorporating uncertain energy prices also demonstrate the economic benefit of procurement management and on-site generation. Yan and Yan (2000) discuss the demand-side bidding and purchase allocation in day-ahead and real-time markets. By using dynamic programming, they find an effective energy purchase strategy that results in lower procurement cost. The same problem is addressed by Liu and Guan (2003) but they also consider the price volatility by including the variance of the cost of purchase in the objective function. They provide an analytical solution to optimal demand bids. Conejo and Carrión (2006) approach the same problem as Conejo et al. (2005), but they consider pool price volatility as well. By applying a mean-variance methodology, they minimise the procurement cost of a large consumer while limiting the risk of its cost variability. Siddiqui and Marnay (2008) also use real options to evaluate the investment decision of a hypothetical California-based microgrid with gas-fired DG. They study separately the effect of stochastic long-term gas prices, operational flexibility (i.e., the option of islanding from the macrogrid), and uncertain electricity prices. Siddiqui and Marnay (2008) find that both high electricity price volatility and operational flexibility increase the value of the project.

While Conejo and Carrión (2006) and Siddiqui and Marnay (2008) take into account market uncertainties, they do not address the operational risk of a consumer. One of the main mathematical tools used to model decision making under uncertainty is stochastic programming. Kettunen et al. (2010) use stochastic programming to examine the optimal operation of an electricity retailer that faces price and demand uncertainties. Pineda (2008) models the decision problem of a power producer company with stochastic electricity spot prices and uncertain availability of the generating units. Carrión et al. (2007) consider the same procurement problem as Conejo et al. (2005) and Conejo and Carrión (2006) but via stochastic programming. They find that as risk aversion increases, the consumer purchases less electricity from the spot market relying more on monthly contracts while the share of on-site generation only slightly decreases.

Our research contributes to the existing literature as follows. Similarly to Carrión et al. (2007), we examine a large consumer, but we also study the use of CHP in addition to a microturbine without heat recovery. Furthermore, we assume that both electricity and gas spot prices are uncertain and futures prices are marked-to-market in every period. Similarly to our optimal DER selection problem, we provide insights into the interaction of financial hedges and on-site generation, but we focus on a microgrid's risk management in the medium term instead of its long-term investment decisions. We find that on-site generation with a CHP unit increases the demand for monthly gas futures significantly compared to on-site generation with an MT and a boiler unit. In addition, operating

CHP can substitute entirely off-peak monthly and weekly base load electricity futures, but it has less effect on monthly base load futures purchases.

3.3 Decision-Making Framework

3.3.1 Assumptions

We address the operation of a microgrid over a one-month time horizon that comprises four weeks. Each week is subdivided into T time periods of equal duration. The microgrid consists of a gas-fired microturbine with heat recovery, a boiler unit, and deterministic electricity and heat loads. The microgrid can purchase electricity from the spot market and from the weekly and monthly futures markets. The monthly electricity futures have either an off-peak load, a peak load, or a base load profile, while the weekly electricity futures contracts can be purchased for base load and peak load periods. The microgrid can also generate electricity using gas from the spot and monthly futures markets while recovering waste heat. When the CHP unit is not in operation, the microgrid employs its boiler unit to meet its heat demand using gas from the spot and monthly futures markets. The microgrid's objective is to minimise the expected value of its procurement cost while limiting its volatility through incorporating risk aversion measured by CVaR.

To reduce computational complexity, we approximate the true distribution of the random electricity and gas prices by an approximation in the form of a five-stage scenario tree (Fig. 3.1) in which each non-root node corresponds to a state of the world spanning one week. Each node of the tree represents a point at which decisions are taken based on the realisation of the random parameters up to the stage of that node. Note that in our nodal formulation the non-anticipativity constraints are incorporated implicitly, i.e., before the scenario tree branches, we do not know at which node we will be at the next stage. A path in the tree from the root (i.e., first-stage) node to a node at the last stage represents a scenario.

The microgrid's decision sequence is as follows. At stage 1, the microgrid chooses how many monthly and week-1 electricity and gas futures it purchases. At stage 2, the microgrid observes the realised spot prices for week 1. Depending on how much electricity and gas it purchased from the futures markets, it then decides, for each subperiod of week 1, how much electricity and gas to purchase on the spot markets, how much electricity to produce on-site, and whether to meet the heat demand using the boiler or heat recovery. While there are no monthly futures purchases at stages 2–5, the weekly futures and spot decision-making procedure is repeated analogously for the remaining three weeks. Finally, as this paper concerns only the operational decisions of a microgrid, we disregard capital costs of the on-site generation units.

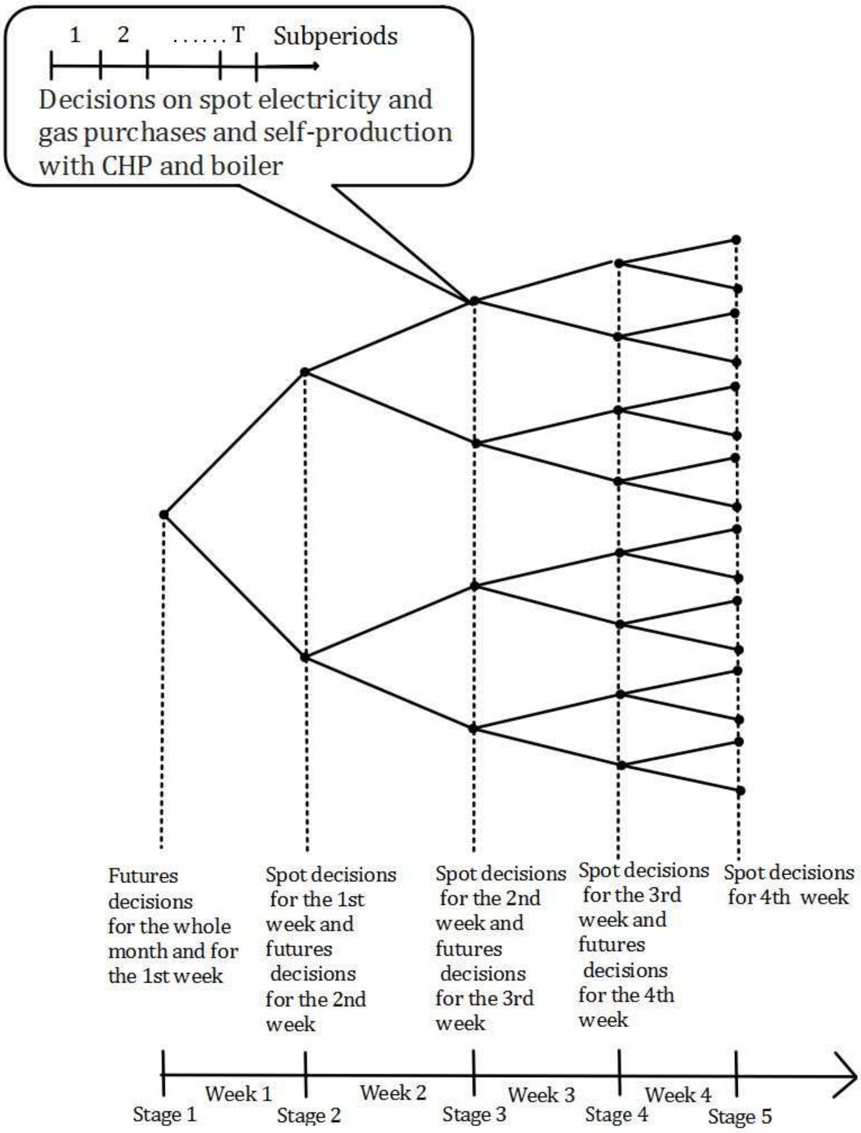


Figure 3.1: Scenario Tree

3.3.2 Nomenclature

Sets and Indices

$a(n)$: ancestor node of node $n \in \mathcal{N}_{-1}$

$\mathcal{C} := \{b, o, p\}$: set of futures contracts in terms of load profile, which can be either base (b), off-peak (o), or peak load (p)

$\mathcal{D}_n$: descendant nodes of node $n \in \mathcal{N}$

$\mathcal{N}$: set of nodes in the scenario tree

$\mathcal{N}_{-1}$: subset of nodes excluding the root node in the scenario tree, i.e., $\mathcal{N}_{-1} := \mathcal{N} \setminus \{1\}$

$\mathcal{N}_s$: set of nodes that scenario $s \in \mathcal{S}$ passes through

$\mathcal{S}$: set of scenarios, i.e., $s \in \mathcal{S}$ is a path from the root node ($n = 1$) to a node at the last stage $W + 1$

$\mathcal{T} := \{1, ..., T\}$: set of time periods at each node $n \in \mathcal{N}_{-1}$

$\mathcal{T}_c$: set of time periods with load profile $c \in \mathcal{C}$ at each node $n \in \mathcal{N}_{-1}$
$\hat{\mathcal{T}} := \{1, \ldots, T \cdot W\}$: auxiliary set of time periods for electricity spot price scenario generation
$\tilde{\mathcal{T}} := \{1, \ldots, \frac{T}{2} \cdot W\}$: auxiliary set of time periods for gas spot price scenario generation
$\mathcal{W} := \{1, ..., W+1\}$: set of stages

Random Parameters

$F^e_{c,a(n)}$: price of weekly electricity futures contracts of type $c \in \mathcal{C}$ fixed in node $a(n)$, $n \in \mathcal{N}_{-1}$, for delivery in the coming week (€/MWh$_\mathrm{e}$)
$P^e_{n,t}$: spot price of electricity at node $n \in \mathcal{N}_{-1}$ in time period $t \in \mathcal{T}$ (€/MWh$_\mathrm{e}$)
$P^g_{n,t}$: spot price of gas at node $n \in \mathcal{N}_{-1}$ in time period $t \in \mathcal{T}$ (€/MWh)

Fixed Parameters

$\epsilon^e_{\hat{t}}$: error term of the ARIMA model for electricity spot prices in time period $\hat{t} \in \hat{\mathcal{T}}$ (€/MWh$_\mathrm{e}$)
$\epsilon^g_{\tilde{t}}$: error term of the dynamic regression model for gas spot prices in time period $\tilde{t} \in \tilde{\mathcal{T}}$ (€/MWh)
ζ, μ_k, ψ_k: parameters used in the dynamic regression model for gas spot prices, $k \in \mathbb{N}$
$\theta_k, \Theta_k, \phi_k, \Phi_k$: parameters used in the ARIMA model for electricity spot prices, $k \in \mathbb{N}$
$\Pi^\mathrm{e}_{m,c}, \Pi^\mathrm{e}_{w,c}$: risk premia of monthly and weekly electricity futures contracts of type $c \in \mathcal{C}$
Π^g_m: risk premium of monthly gas futures contracts
$\sigma^\mathrm{e}, \sigma^\mathrm{g}$: standard deviations of the error term of the electricity and gas price processes
A: confidence level for the CVaR
B: risk weight
E^b: boiler conversion efficiency, i.e., volume of useful heat produced from one MWh of natural gas (MWh/MWh)
E^e: electrical conversion efficiency, i.e., volume of electricity produced from one MWh of natural gas (MWh$_\mathrm{e}$/MWh)
E^h: heat-recovery rate from on-site generation, i.e., volume of useful heat captured while producing one MWh$_e$ of electricity (MWh/MWh$_\mathrm{e}$)
$D^e_{w(n),t}$: electricity load in stage $w(n) \in \mathcal{W}$, $n \in \mathcal{N}_{-1}$, and period $t \in \mathcal{T}$ (MW$_\mathrm{e}$)
$D^h_{w(n),t}$: heat load in stage $w(n) \in \mathcal{W}$, $n \in \mathcal{N}_{-1}$, and period $t \in \mathcal{T}$ (MW)
$H_{c,w(n),t}$: length of energy delivery by a contract of type $c \in \mathcal{C}$ in stage $w(n) \in \mathcal{W}$, $n \in \mathcal{N}_{-1}$, in period $t \in \mathcal{T}$ (h)
$J_{w(n),t}$: length of time period $t \in \mathcal{T}$ in stage $w(n) \in \mathcal{W}$, $n \in \mathcal{N}_{-1}$ (h)
K^b: capacity of the boiler unit (MW)
K^e: capacity of electricity generation unit (MW$_e$)
L^e_c: price of monthly electricity futures contracts of type $c \in \mathcal{C}$ (€/MWh$_\mathrm{e}$)

L^g: price of monthly gas futures contracts (€/MWh)
$\hat{P}^e_{\hat{t}}$: spot price of electricity in time period $\hat{t} \in \hat{\mathcal{T}}$ used for electricity spot price scenario generation; $\hat{P}^e_{s,\hat{t}}$ for scenario $s \in \mathcal{S}$ (€/MWh$_\mathrm{e}$)
$\tilde{P}^e_{\tilde{t}}$: spot price of electricity in time period $\tilde{t} \in \tilde{\mathcal{T}}$ used for gas spot price scenario generation; $\tilde{P}^e_{s,\tilde{t}}$ for scenario $s \in \mathcal{S}$ (€/MWh$_\mathrm{e}$)
$\tilde{P}^g_{\tilde{t}}$: spot price of gas in time period $\tilde{t} \in \tilde{\mathcal{T}}$ used for gas spot price scenario generation; $\tilde{P}^g_{s,\tilde{t}}$ for scenario $s \in \mathcal{S}$ (€/MWh)
q_s: probability of scenario path $s \in \mathcal{S}$
$w(n) \in \mathcal{W}$: stage of node $n \in \mathcal{N}$

Decision Variables

γ_s: cost of satisfying the electricity and heat loads in scenario path $s \in \mathcal{S}$ (€)
η_s: auxiliary variable to estimate the conditional value-at-risk (CVaR) in scenario path $s \in \mathcal{S}$ (€)
ξ: VaR at confidence level A (€)
$x^\mathrm{b}_{n,t}$: gas purchased from the spot market for boiler heat production in node $n \in \mathcal{N}_{-1}$ during period $t \in \mathcal{T}$ (MWh)
$x^\mathrm{e}_{n,t}$: electricity purchased on the spot market in node $n \in \mathcal{N}_{-1}$ during period $t \in \mathcal{T}$ (MWh$_\mathrm{e}$)
$x^\mathrm{g}_{n,t}$: gas purchased on the spot market for on-site electricity generation in node $n \in \mathcal{N}_{-1}$ during period $t \in \mathcal{T}$ (MWh)
$y^\mathrm{e}_{c,a(n)}$: electricity delivered by weekly futures of type $c \in \mathcal{C}$ in node $n \in \mathcal{N}_{-1}$ (MW$_\mathrm{e}$)
z^b: natural gas delivered by monthly futures for boiler heat production during the whole month (MW)
z^e_c: electricity delivered by monthly futures of type $c \in \mathcal{C}$ during the whole month (MW$_\mathrm{e}$)
z^g: natural gas delivered by monthly futures for on-site electricity generation during the whole month (MW)

3.3.3 Model Formulation

Objective Function

The objective function in Eq. (3.1) minimises the sum of the expected value (first term) and a weighted CVaR of the cost of running the microgrid (second term:

$$\text{minimise} \sum_{s \in \mathcal{S}} q_s \gamma_s + B\Big(\xi + \frac{1}{1-A} \sum_{s \in \mathcal{S}} q_s \eta_s\Big) \tag{3.1}$$

Constraints

Eqs. (3.2)–(3.3) are necessary for calculating the CVaR of the cost of running the microgrid up to the end of the time horizon, $\forall s \in \mathcal{S}$:

$$\gamma_s - \xi - \eta_s \leq 0 \tag{3.2}$$

$$\eta_s \geq 0 \tag{3.3}$$

Eq. (3.4) calculates the cost of running the microgrid in scenario $s \in \mathcal{S}$:

$$\begin{aligned}\gamma_s = &\sum_{n\in\mathcal{N}_s\setminus\{1\}}\sum_{t\in\mathcal{T}}\Big(\sum_{c\in\mathcal{C}}(z^{\mathrm{e}}_c L^e_c H_{c,w(n),t} + y^{\mathrm{e}}_{c,a(n)} F^e_{a(n)} H_{c,w(n),t})\\ &+ x^{\mathrm{e}}_{n,t} P^e_{n,t} + (z^{\mathrm{g}} + z^{\mathrm{b}}) L^g J_{w(n),t} + (x^{\mathrm{g}}_{n,t} + x^{\mathrm{b}}_{n,t}) P^g_{n,t}\Big)\end{aligned} \tag{3.4}$$

Eqs. (3.5)–(3.6) ensure that the electricity and heat demands are met at all time, $\forall n \in \mathcal{N}_{-1}, \forall t \in \mathcal{T}$:

$$\begin{aligned}&x^{\mathrm{e}}_{n,t} + \sum_{c\in\mathcal{C}}(y^{\mathrm{e}}_{c,a(n)} H_{c,w(n),t} + z^{\mathrm{e}}_c H_{c,w(n),t})\\ &+ E^e(x^{\mathrm{g}}_{n,t} + z^{\mathrm{g}} J_{w(n),t}) \geq D^e_{w(n),t}\end{aligned} \tag{3.5}$$

$$\begin{aligned}&E^h E^e(x^{\mathrm{g}}_{n,t} + z^{\mathrm{g}} J_{w(n),t})\\ &+ E^b(x^{\mathrm{b}}_{n,t} + z^{\mathrm{b}} J_{w(n),t}) \geq D^h_{w(n),t}\end{aligned} \tag{3.6}$$

Eqs. (3.7)–(3.8) ensure that the DER and boiler capacity limits are observed, $\forall n \in \mathcal{N}_{-1}, \forall t \in \mathcal{T}$:

$$E^e(x^{\mathrm{g}}_{n,t} + z^{\mathrm{g}} J_{w(n),t}) \leq K^e J_{w(n),t} \tag{3.7}$$

$$E^b(x^{\mathrm{b}}_{n,t} + z^{\mathrm{b}} J_{w(n),t}) \leq K^b J_{w(n),t} \tag{3.8}$$

Finally, all of the purchase decision variables must be non-negative, $\forall n \in \mathcal{N}_{-1}, \forall t \in \mathcal{T}, \forall c \in \mathcal{C}$:

$$\begin{aligned}&x^{\mathrm{e}}_{n,t} \geq 0, x^{\mathrm{g}}_{n,t} \geq 0, x^{\mathrm{b}}_{n,t} \geq 0, y^{\mathrm{e}}_{c,a(n)} \geq 0,\\ &z^{\mathrm{e}}_c \geq 0, z^{\mathrm{g}} \geq 0, z^{\mathrm{b}} \geq 0\end{aligned} \tag{3.9}$$

3.4 Numerical Examples

While Germany is one of the largest CHP markets in the world, the share of cogeneration in its electricity production at 14.5% is still relatively low compared to other European countries, such as The Netherlands and Denmark with a 30% and a 53% share, respectively. Germany, with similar weather conditions to The Netherlands and Denmark, has a huge potential to increase its CHP generation both in the residential and commercial sectors (BMU, 2007). Furthermore, additional CHP capacity can also contribute to efficient and more reliable energy supply to counteract the growing intermittent production. Consequently, the German government has set a target to raise the level of electricity produced by CHP to 25% by 2020. To examine how operational risk from energy price uncertainties can be managed in a microgrid in Germany, we solve the optimisation problem using German electricity and gas spot and futures prices. For all risk-averse optimisations, a confidence level of $A = 95\%$ is used in the calculation of CVaR.

3.4.1 Spot Market Data

The parameters to generate the electricity and gas price scenarios are estimated using data from the European Energy Exchange's (EEX) German electricity and gas spot markets between 1 January 2010 and 2 December 2012 (Fig. 3.2). We use the hourly electricity spot prices to calculate the daily average peak (8 AM–8 PM) and off-peak (8 PM–8 AM) prices ($\hat{P}^{\mathrm{e}}_{\hat{t}}$). By using a daily peak and off-peak ($T = 14$) instead of an hourly ($T = 168$) granularity, we keep our problem tractable while capturing the daily variability of the electricity price.

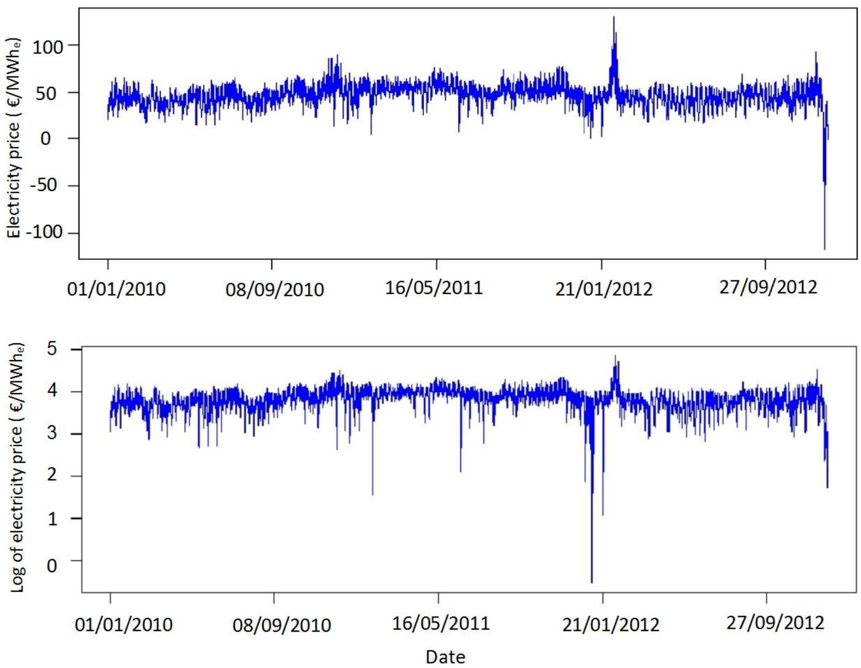


Figure 3.2: German Off-Peak and Peak Load the Electricity Prices and the Logarithm of the Prices

We assume that electricity prices can be described by a seasonal autoregressive integrated moving average (ARIMA) process because it takes into account the seasonal patterns and periods of volatility that electricity prices typically exhibit (Weron, 2007; Cowpertwait and Metcalfe, 2009). In ARIMA models, autoregression terms express that the modelled variable depends linearly on its previous values, while the moving average terms incorporate the effect of previous error terms. Once we decide how many seasonal, autoregressive and moving average terms to use, we fit the model using maximum likelihood function with starting values minimising the conditional sum of squared errors (Box and Jenkins, 1976). Seasonal ARIMA models can be substantially large in terms of the number and combination of terms. Thus, we estimate the number of (seasonal and non-seasonal) autoregressive and moving average terms iteratively by comparing the Akaike information criterion (Cowpertwait and Metcalfe, 2009). The parameters of the ARIMA process are given in Table 3.1. Both the autocorrelation and partial autocorrelation function demonstrate that the peak and off-peak electricity prices follow strong weekly seasonality (Figs. 3.3-3.4), which equals to a 14-period seasonality.

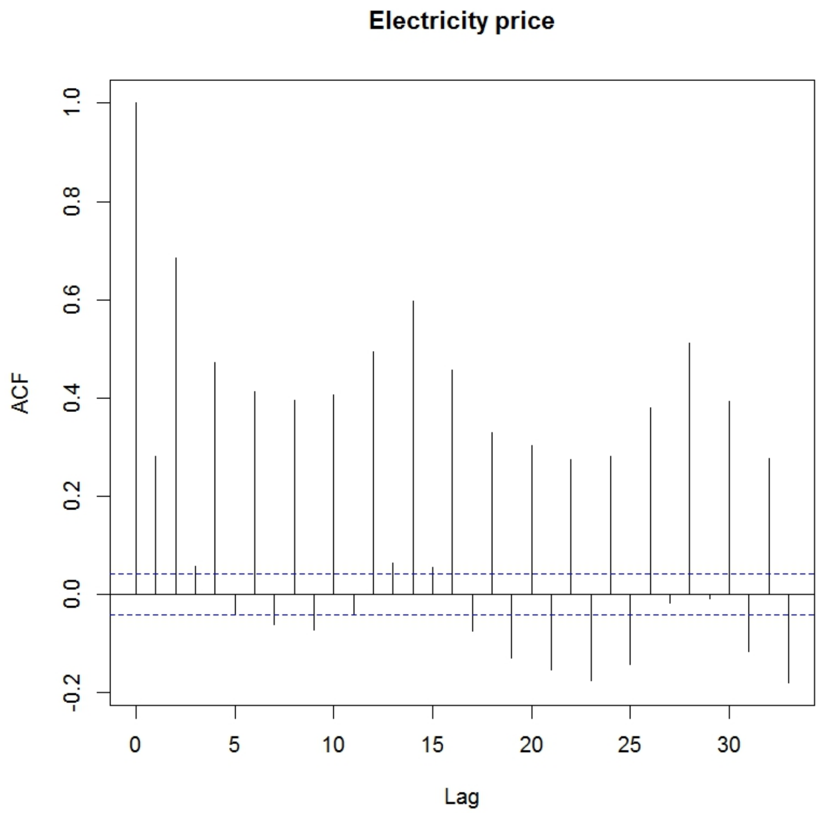


Figure 3.3: Partial Autocorrelation Function of the Electricity Price

As Fig. 3.5 shows, the selected model resulted in residuals that are approximately white noise.

Thus, we find that the following seasonal ARIMA process provides the best fit to the

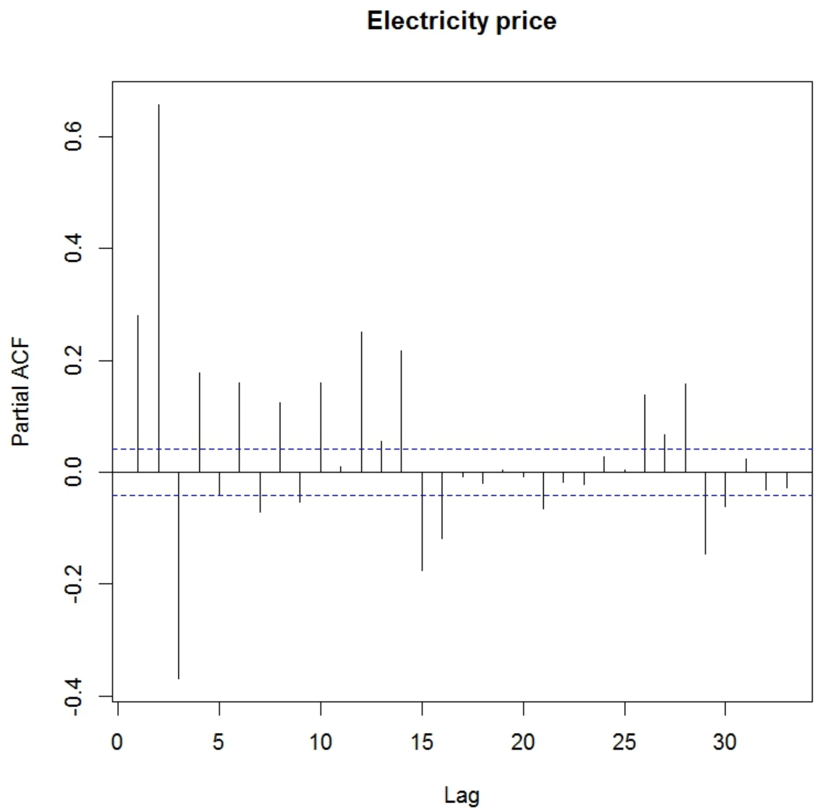


Figure 3.4: Autocorrelation Function of the Electricity Price

electricity prices $\hat{P}^{\mathrm{e}}_{\hat{t}}, \hat{t} \in \hat{\mathcal{T}} := \{1, \ldots, T \cdot W\}$:

$$(1 - \phi_1 - \phi_2 - \phi_3)(1 - \Phi_1 B^{14})(1 - B)(1 - B^{14})\hat{P}^{\mathrm{e}}_{\hat{t}} = (1 + \theta_1 + \theta_2 + \theta_3 + \theta_4)(1 + \Theta_1 B^{14} + \Theta_2 B^{15})\epsilon^{\mathrm{e}}_{\hat{t}}. \tag{3.10}$$

Here, we apply the backshift operator B^k to specify lagged prices, i.e., $B^k \hat{P}^{\mathrm{e}}_{\hat{t}} = \hat{P}^{\mathrm{e}}_{\hat{t}-k}$, and we assume that $\epsilon^{\mathrm{e}}_{\hat{t}}, \hat{t} \in \hat{\mathcal{T}}$, are independent and identically distributed normal random variables with zero mean and constant standard deviation σ^{e}.

The gas price ($\tilde{P}^{\mathrm{g}}_{\tilde{t}}$) is assumed to follow a dynamic regression process dependent on the generated electricity price. Since gas spot prices have a daily granularity, we calculate the daily electricity price using the average of the respective peak and off-peak prices, $\forall \tilde{t} \in \tilde{\mathcal{T}} := \{1, \ldots, \frac{T}{2} \cdot W\}$:

$$\tilde{P}^{\mathrm{e}}_{\tilde{t}} = \frac{\hat{P}^{\mathrm{e}}_{2\tilde{t}-1} + \hat{P}^{\mathrm{e}}_{2\tilde{t}}}{2}. \tag{3.11}$$

The best fit to the daily gas spot prices $\tilde{P}^{\mathrm{g}}_{\tilde{t}}, \tilde{t} \in \tilde{\mathcal{T}}$, is the following dynamic regression

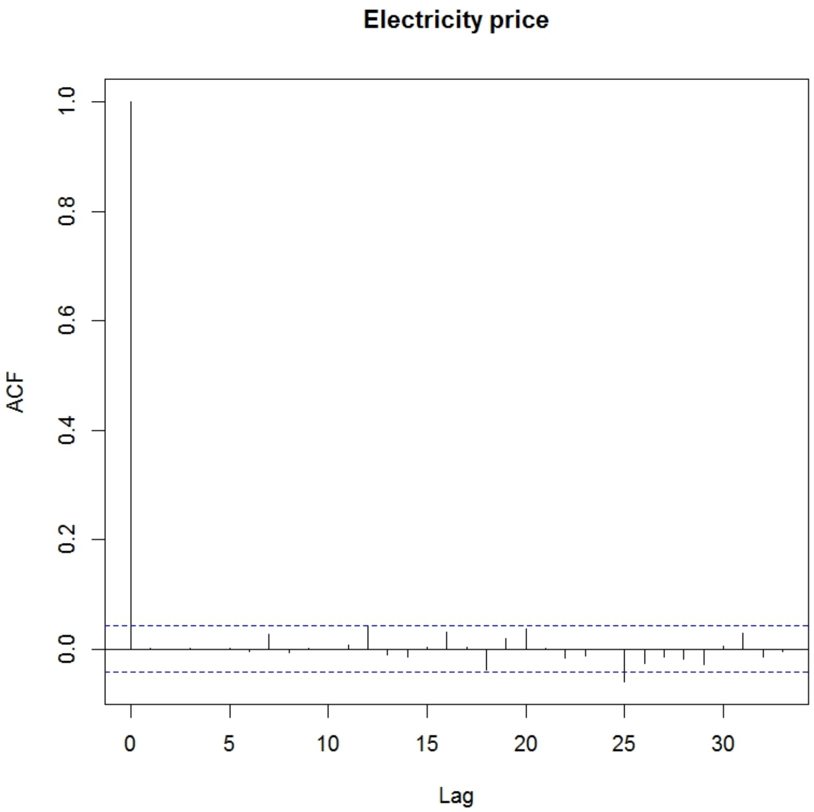


Figure 3.5: Autocorrelation Function of the Residuals

model:

$$\tilde{P}^{\mathrm{g}}_{\tilde{t}} = \zeta + \mu_1 \tilde{P}^{\mathrm{g}}_{\tilde{t}-1} + \mu_4 \tilde{P}^{\mathrm{g}}_{\tilde{t}-4} + \mu_6 \tilde{P}^{\mathrm{g}}_{\tilde{t}-6} \\ + \psi \tilde{P}^{\mathrm{e}}_{\tilde{t}} + \psi_3 \tilde{P}^{\mathrm{e}}_{\tilde{t}-3} + \psi_5 \tilde{P}^{\mathrm{e}}_{\tilde{t}-5} + \epsilon^{\mathrm{g}}_{\tilde{t}}, \tag{3.12}$$

where we assume that $\epsilon^{\mathrm{g}}_{\tilde{t}}, \tilde{t} \in \tilde{\mathcal{T}}$, are mutually independent and identically distributed normal random variables with zero mean and constant standard deviation σ^{g}, and independent from $\epsilon^{\mathrm{e}}_{\hat{t}}, \hat{t} \in \hat{\mathcal{T}}$. The estimated parameters of process (3.10) and (3.12) are displayed in Table 3.1.

For our numerical example, we build a scenario tree with seven branches per non-terminal node, resulting in a total of $S = 2401$ scenarios. To examine the stability of the scenario tree, we run the optimisation problem of a risk-neutral consumer for additional scenario trees, with branches ranging from 3 to 7, each of them ten times. We find that with seven branches, the stability of the expected running cost is adequate, i.e., the standard deviation of the average expected cost is small, therefore, we deem 2401 scenarios sufficient. To construct the scenario tree, we sample S electricity price paths $\{\hat{P}^{\mathrm{e}}_{s,\hat{t}}\}_{\hat{t}\in\hat{\mathcal{T}}}, s \in \mathcal{S} := \{1, \ldots, S\}$, from process (3.10) and corresponding S gas price paths $\{\tilde{P}^{\mathrm{g}}_{s,\tilde{t}}\}_{\tilde{t}\in\tilde{\mathcal{T}}}, s \in \mathcal{S}$, from process (3.12). These scenario paths are then used to construct the scenario tree according to the following relations, $\forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}_s \setminus \{1\}$:

$$P^{\mathrm{e}}_{n,t} = \hat{P}^{\mathrm{e}}_{s,t+T[w(n)-2]} \tag{3.13}$$

$$P^{\mathrm{g}}_{n,t} = \begin{cases} \tilde{P}^{\mathrm{g}}_{s,\frac{t}{2}+\frac{T}{2}[w(n)-2]} & \text{if } t \text{ is even} \\ \tilde{P}^{\mathrm{g}}_{s,\frac{t+1}{2}+\frac{T}{2}[w(n)-2]} & \text{if } t \text{ is odd} \end{cases} \tag{3.14}$$

Note that, while we generate gas prices for $\frac{T}{2} \cdot W$ periods, the scenario tree contains $T \cdot W$ time periods. For this reason, Eq. (3.14) assigns the same gas price to consecutive peak and off-peak periods. Furthermore, to obtain a valid scenario tree, electricity and gas prices at a given time period, but in different scenarios s and s' have to be equal if they share the same history of observations. In other words, the relations $\hat{P}^{\mathrm{e}}_{s,\hat{t}} = \hat{P}^{\mathrm{e}}_{s',\hat{t}}$ $\left(\tilde{P}^{\mathrm{g}}_{s,\tilde{t}} = \tilde{P}^{\mathrm{g}}_{s',\tilde{t}}\right)$ must be enforced if scenarios s and s' pass through the same nodes up to and including the stage of time period $\hat{t} \in \hat{\mathcal{T}}$ $\left(\tilde{t} \in \tilde{\mathcal{T}}\right)$. To provide a quick overview of the results of the scenario generation, Figure 3.7 presents pairs of electricity and gas prices (red circles) from generated 2401 scenarios and pairs of daily gas and peak or off-peak load electricity prices (black squares) recorded between January 2010 and December 2012. While most of historical data are within the area covered by generated scenarios, they tend to correspond to lower prices. The reason for this is that the generated scenarios represent winter prices, which are usually higher, while historical data cover the whole year. Nevertheless, our model seems to capture adequately both the correlation between and the range of electricity and gas prices.

Table 3.1: Estimated Process Parameters for Electricity and Gas Prices

$\phi_1 = -0.7612$	$\theta_3 = -0.1612$
$\phi_2 = 0.4368$	$\theta_4 = -0.1584$
$\phi_3 = 0.2010$	$\Theta_1 = -0.0897$
$\Phi_1 = -0.8610$	$\Theta_2 = -0.8714$
$\theta_1 = 0.2168$	$\sigma^{\mathrm{e}} = 43.40$
$\theta_2 = -0.7014$	
$\zeta = 0.5820$	$\psi = 0.0183$
$\mu_1 = 0.9397$	$\psi_3 = -0.0106$
$\mu_4 = -0.8830$	$\psi_5 = -0.0126$
$\mu_6 = 0.1343$	$\sigma^{\mathrm{g}} = 0.8206$

3.4.2 Forward Market Data

One of the main requirements for generation price scenarios is to provide an arbitrage-free pricing environment (Klaassen, 2002), i.e., it is not possible to decrease both the CVaR and expected cost at the same time by purchasing futures. Thus, to maintain the no-arbitrage principle, we calculate the gas and electricity futures prices using the corresponding average spot prices and risk premia as follows, for all $c \in \mathcal{C}$ and all non-

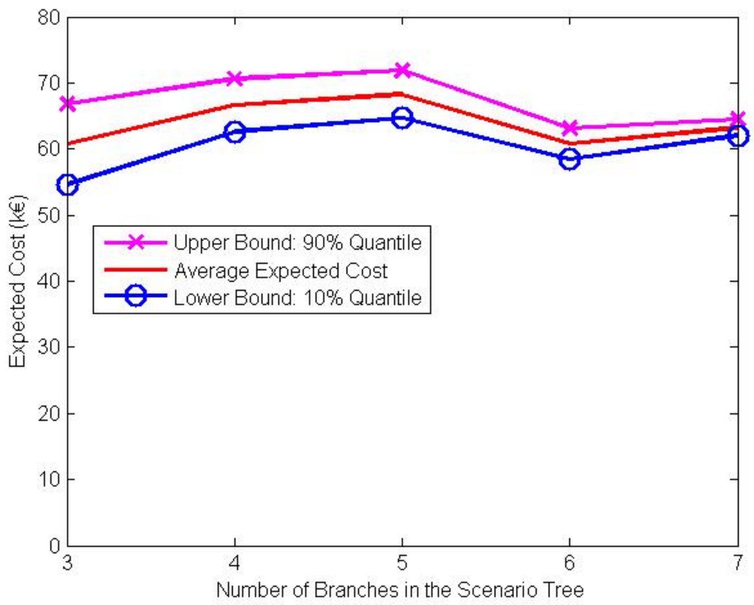


Figure 3.6: 90% Confidence Interval of the Average Expected Cost in the Risk-Neutral Regime

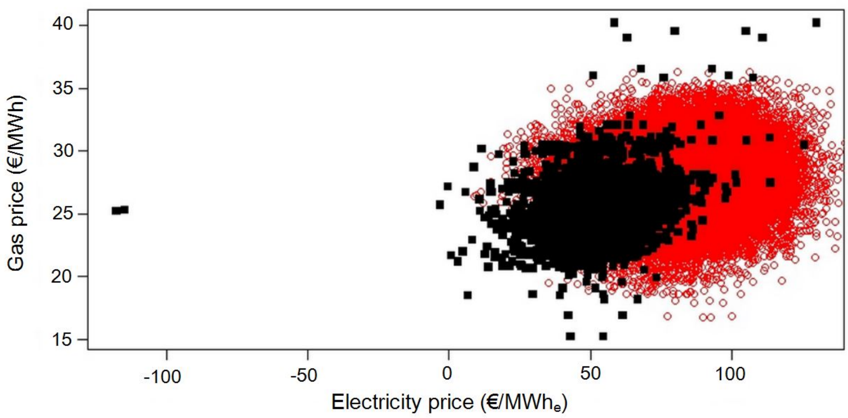


Figure 3.7: Generated Scenarios of Electricity and Natural Gas Prices Historical Data From January 2010 to December 2012

terminal nodes $n \in \mathcal{N}$:

$$F^e_{c,n} = \left(\frac{1}{|\mathcal{D}_n|}\sum_{n'\in\mathcal{D}_n}\frac{1}{|\mathcal{T}_c|}\sum_{t\in\mathcal{T}_c}P^e_{n',t}\right)(1+\Pi^{\mathrm{e}}_{w,c}) \tag{3.15}$$

$$L^e_c = \left(\frac{1}{|\mathcal{N}_{-1}|}\sum_{n\in\mathcal{N}_{-1}}\frac{1}{|\mathcal{T}_c|}\sum_{t\in\mathcal{T}_c}P^e_{n,t}\right)(1+\Pi^{\mathrm{e}}_{m,c}) \tag{3.16}$$

$$L^g = \left(\frac{1}{|\mathcal{N}_{-1}|}\sum_{n\in\mathcal{N}_{-1}}\frac{1}{|\mathcal{T}|}\sum_{t\in\mathcal{T}}P^g_{n,t}\right)(1+\Pi^{\mathrm{g}}_{m}) \tag{3.17}$$

The risk premia for gas and electricity futures are calculated from the EEX Phelix and Natural Gas Futures markets and the corresponding spot prices from the 2011–2012 period (Table 3.2). Note that, in accordance with the Phelix market, only monthly electricity futures have off-peak load profiles. The electricity and heat loads are based on a typical winter energy consumption of a small hospital provided by Energy Systems Research Unit at the University of Strathclyde (Fig. 3.8).

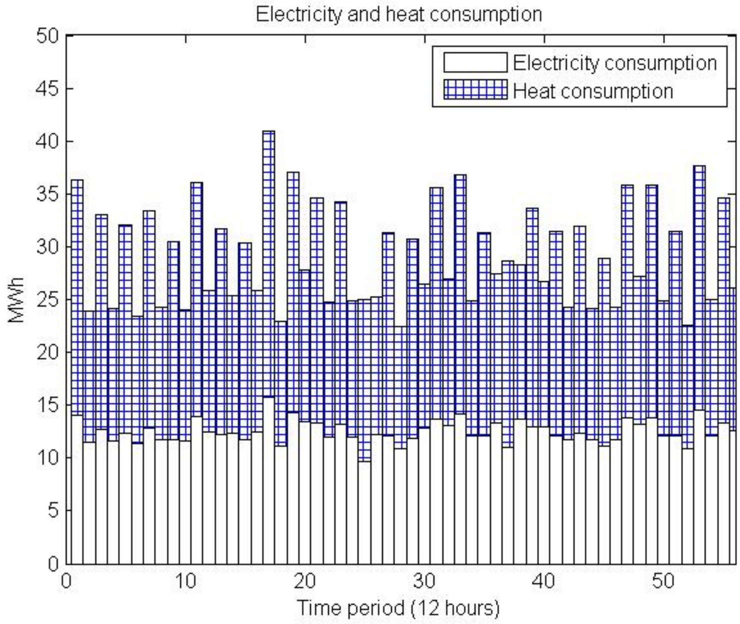


Figure 3.8: Electricity and Heat Consumption

Table 3.2: Risk Premia for Futures

$\Pi^{\mathrm{e}}_{m,b} = 0.021$	$\Pi^{\mathrm{e}}_{w,b} = 0.009$
$\Pi^{\mathrm{e}}_{m,o} = 0.020$	$\Pi^{\mathrm{e}}_{w,p} = 0.041$
$\Pi^{\mathrm{e}}_{m,p} = 0.083$	$\Pi^{\mathrm{g}}_{m} = 0.004$

3.4.3 Technology Data

We compare the optimal operation of the microgrid with no on-site generation, with on-site generation without heat recovery (MT), and with on-site generation with heat recovery (CHP). The electrical conversion efficiency (E^e) of the microturbines is 35%, and the CHP's heat-recovery rate ($E^e \cdot E^h$) is 52.5%, while the boiler's conversion efficiency (E^b) is 90%. These parameters are in line with Moran et al. (2008), Siddiqui et al. (2005), and Wickart and Madlener (2007). Finally, we consider on-site generation at 300 $\mathrm{kW_e}$, 600 $\mathrm{kW_e}$, and 900 $\mathrm{kW_e}$ capacity levels.

3.5 Results

3.5.1 Main Insights

The optimisation problems are implemented in the General Algebraic Modeling System (GAMS) using GUROBI solver on Windows workstation with an Intel Core i7 3.3GHz

CPU and 16 GB RAM. The computational times range from 13 to 278 seconds. Our results support previous findings that, compared to purchasing electricity from the main grid, on-site generation with CHP reduces significantly the microgrid's expected energy cost, contributes to higher energy efficiency, and, hence, to lower CO_2 emissions. In addition, we find that on-site generation with CHP can decrease the microgrid's CVaR and, consequently, can function as a physical hedge against financial risk. Using on-site generation reduces both the expected running cost of the microgrid and its CVaR (Table 3.3). While higher installed capacity results in lower expected cost for both CHP and MT, interestingly, the 300 kW_e CHP unit reduces the expected cost more than even the 900 kW_e MT unit.

Table 3.3: Results for Running the Microgrid under Risk-Neutral Regime ($B = 0$)

Case	Expected cost (k€)	CVaR (k€)	Efficiency of the microgrid	Expected CO_2 emissions (kiloton)
No on-site generation	79.6	86.8	71.2%	0.92
300 kW_e MT	78.7	86.0	69.1%	0.69
600 kW_e MT	77.9	85.2	67.1%	0.86
900 kW_e MT	77.0	84.6	65.2%	0.83
300 kW_e CHP	71.8	78.3	75.1%	0.77
600 kW_e CHP	64.0	70.0	79.5%	0.62
900 kW_e CHP	58.1	64.0	82.2%	0.50

Figs. 3.9 and 3.10 present the histograms of the savings compared to no on-site generation for each scenario. The distributions of the cost reduction with MT are right-skewed with similar central tendencies, whereas with CHP, the distributions of the cost reduction are close to symmetric, and the median saving increases significantly with larger capacity. Thus, with MT, a lower cost reduction is much more likely than with CHP, the use of which can result in small and large cost reductions with similar probabilities.

In terms of CVaR reduction, the difference between MT and CHP is even more pronounced. First, note that the CVaR of the microgrid can be decreased either by reducing the expected cost or by reducing the volatility of the cost of running the microgrid. While MT reduces the CVaR at each capacity level, the CVaR reductions are, in fact, smaller than the reduction in expected cost, i.e., the CVaR relative to the expected cost is increasing. On the contrary, CHP always results in a larger CVaR reduction than the reduction in expected cost. As the standard deviation of the gas spot price is lower than that of the electricity spot price – 4.7% compared to 25.0% – the CHP reduces the CVaR of the microgrid by efficiently swapping electricity for gas. To generate one MWh_e of electricity, both MT and CHP require 2.8 MWh gas, but the CHP unit recovers 1.5 MWh heat at the same time, thereby reducing the microgrid's gas purchases. Since heat consumption is on

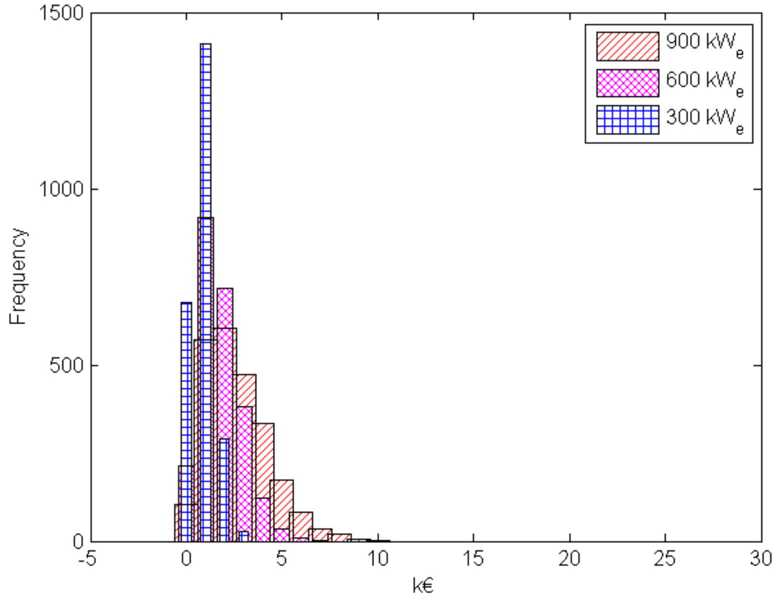


Figure 3.9: Cost Savings with MT Compared to No On-Site Generation

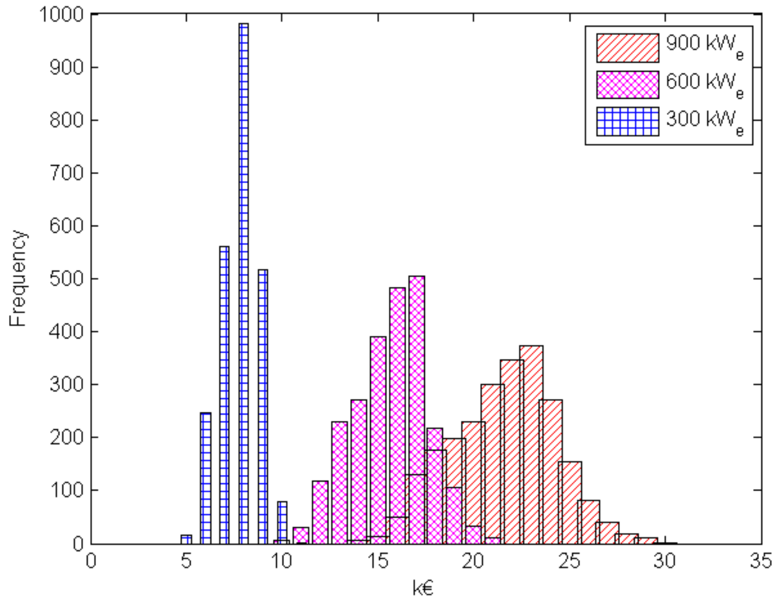


Figure 3.10: Cost Savings with CHP Compared to No On-Site Generation

average 60% higher than the electricity consumption in peak periods, and only 6% larger in off-peak periods, the microgrid uses CHP the most when the electricity price is more volatile. Thus, the CHP not only needs to swap less gas for a MWh_e of electricity but also does this in periods with more volatile electricity prices. This is why the reduction in relative standard deviation for each scenario is much lower with MT (Fig. 3.11) than with CHP (Fig. 3.12). Due to the high level of heat consumption in peak periods, operating CHP units with larger capacity size results, on average, in a higher level of reduction in relative standard deviation.

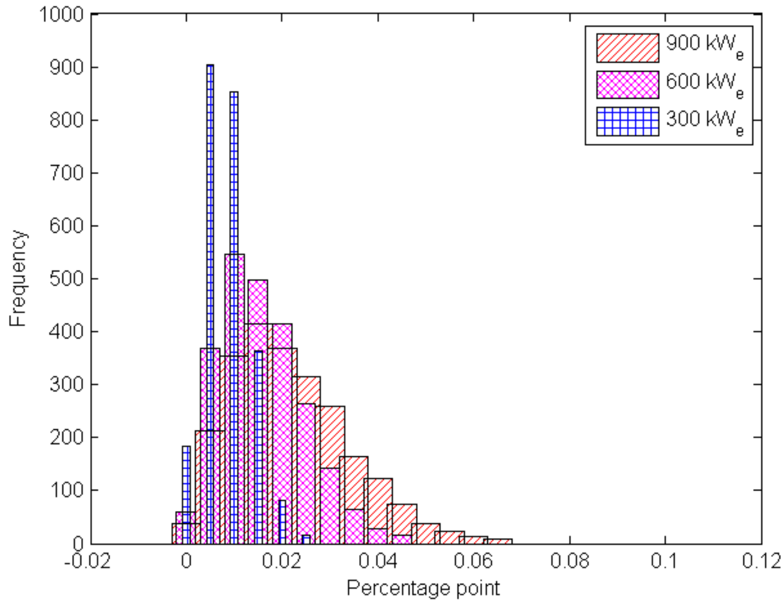


Figure 3.11: Reduction in Relative Standard Deviation with MT Compared to No On-Site Generation

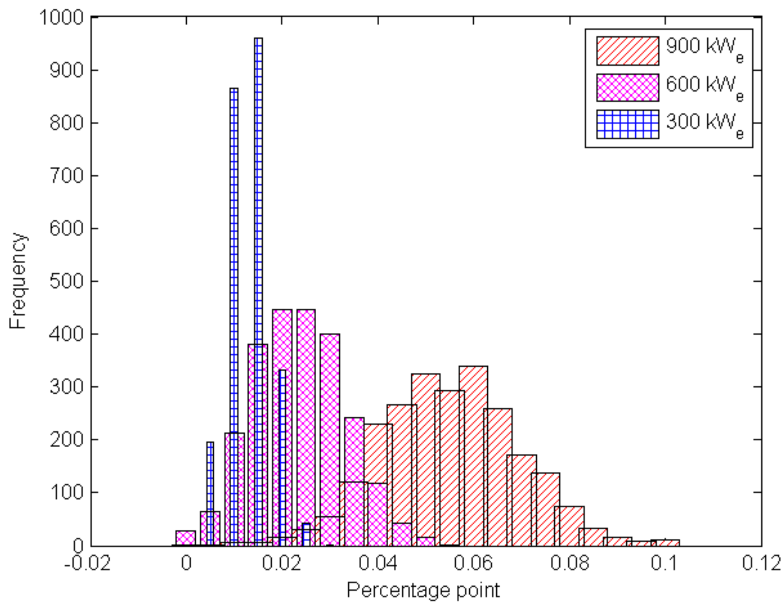


Figure 3.12: Reduction in Relative Standard Deviation with CHP Compared to No On-Site Generation

3.5.2 On-Site Generation with Futures

To examine further the risk-reducing characteristics of on-site generation, we run the microgrid's optimisation model with a 600 kW$_e$ MT or CHP unit together with the option of purchasing electricity and gas futures. We find a strong interaction between on-site generation and financial hedges, i.e., the type of on-site generation determines which futures the microgrid purchases. Fig. 3.13 shows the efficient frontiers of a microgrid with only futures purchases, with MT installation and futures purchases, and with CHP installation and futures purchases. These frontiers are delimited by varying B parameter in order to illustrate the mean-risk tradeoff. First, note that on-site generation with MT on its own (at $B = 0$) has a higher CVaR than a risk-averse microgrid with only futures purchases (at $B = 0.2$), thereby indicating that financial futures are more efficient hedges than an MT. While electricity futures fix the electricity price and can eliminate price volatility, a microgrid with MT needs to buy spot gas at variable price. Although the volatility of gas spot price is much lower than that of the electricity spot price, because of the low total efficiency of MT, the microgrid needs to purchase more spot gas, which results in higher CVaR compared to purchasing only futures. Conversely, a microgrid with a CHP unit has much lower CVaR than the most risk-averse microgrid that buys only futures. In addition, financial futures are more efficient at reducing CVaR together with CHP, i.e., they have lower mean-CVaR tradeoff, which is shown by the flatter efficient frontier.

Considering the microgrid with only financial hedges, Fig. 3.14 indicates that the more risk-averse the microgrid becomes, the more monthly base load futures it purchases. In the most risk-averse regime at $B = 10$, the microgrid's CVaR reduction amounts to €4.9k, which is 5.6% of the CVaR at the risk-neutral regime at $B = 0$. The reason why the microgrid mostly purchases base load contracts is that the hospital's electricity consumption differs only slightly between peak and off-peak periods. Thus, purchasing monthly electricity base load futures, which have lower risk premia than monthly peak load contracts and just slightly higher risk premia than monthly off-peak contracts, provides a cheaper hedge. Similarly, with increasing risk aversion, the microgrid purchases more monthly gas futures for boiler. At its maximum level of risk aversion ($B = 10$), the microgrid meets 73.7% of its heat demand through monthly gas contracts (Fig. 3.15).

In comparison to a microgrid with only futures trading, in a risk-averse microgrid with MT, the share of monthly base load electricity futures decreases significantly and is only non-negligible with higher levels of risk aversion (Fig. 3.16). The microgrid meets on average 20% of its electricity consumption with on-site generation using gas spot. With risk aversion, the share of off-peak monthly futures and weekly base load futures in electricity consumption first increases and later slightly decreases. This indicates that monthly base load futures are substitutes for weekly base load and monthly off-peak load electricity futures. Furthermore, the share of on-site generation with spot gas also decreases slightly from 19.2% at $B = 0$ to 16.5% at $B = 10$. Thus, the microgrid uses its MT well below its capacity limit, which would be 62.5% on average, and, in order to decrease its CVaR, it has to operate the MT less. As using the MT has an undesirable

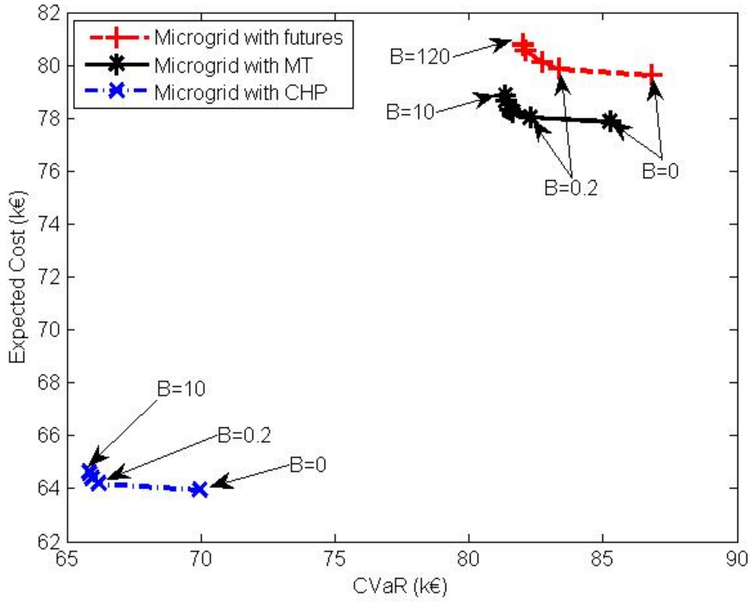


Figure 3.13: Efficient Frontiers with Futures Purchases

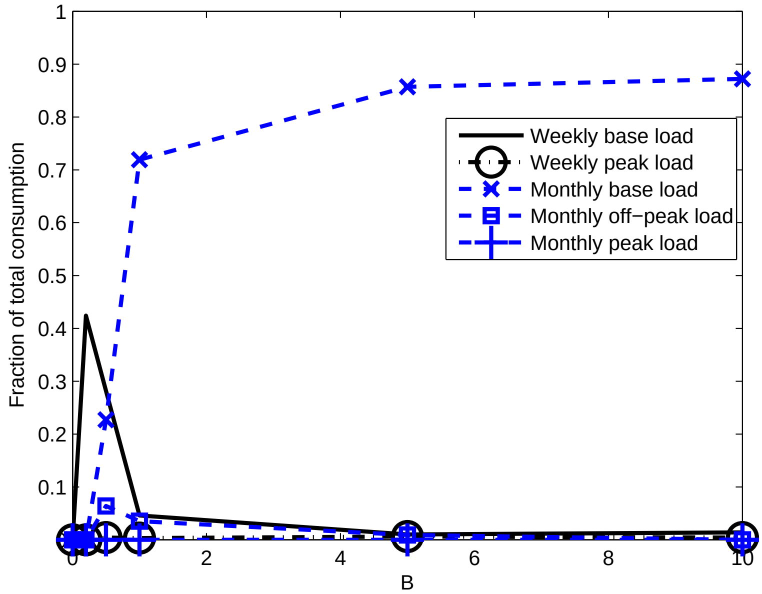


Figure 3.14: Electricity Consumption Without On-Site Generation

effect on the microgrid's CVaR, it purchases electricity futures with the lowest risk premia, such as weekly base load and monthly off-peak load contracts. Since a microgrid with MT can use only the boiler to meet its heat demand, its heat consumption is the same as with no on-site generation, i.e., monthly gas future purchases increases with risk aversion (Fig. 3.15).

Finally, Fig. 3.17 shows the share of on-site generation and futures purchases in the electricity consumption of a microgrid with an installed CHP unit. The presence

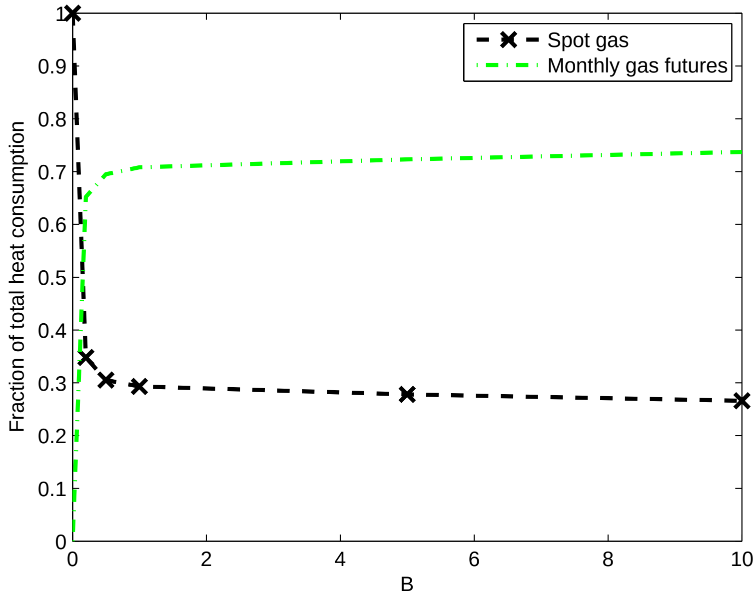


Figure 3.15: Heating Consumption with Only Available Futures

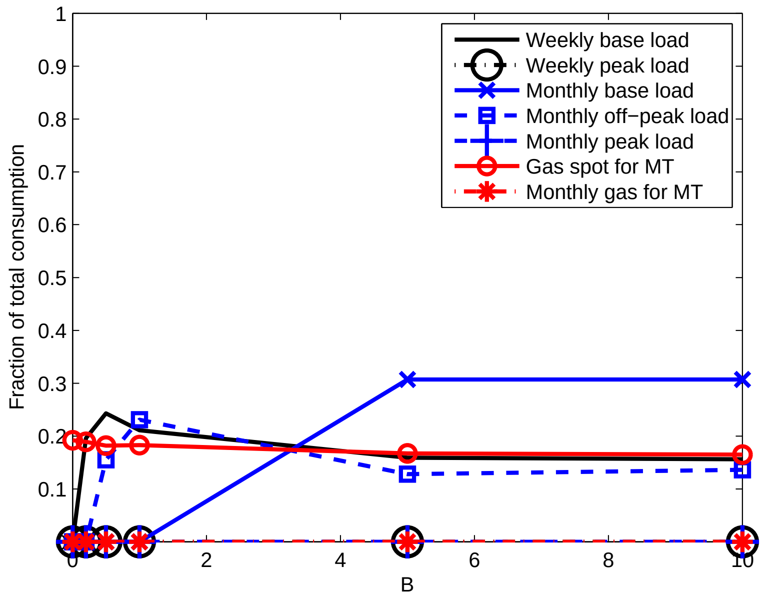


Figure 3.16: Electricity Consumption with MT

of CHP increases the demand for monthly gas futures significantly. An MT unit with lower energy efficiency cannot use monthly gas contracts due to their higher prices, which would negate its achievable cost reduction. A microgrid with a CHP unit, on the other hand, can tolerate the risk premia, and with fixed gas prices, it attains greater CVaR reduction. In fact, the total share of on-site generation with CHP increases from 56.3% at $B = 0$ to 57.7% at $B = 10$. Thus, the CVaR-reducing demand for both gas futures and on-site generation with CHP increase at the same time, which indicates that they are complements. Compared to a microgrid with MT, a microgrid with CHP purchases almost no off-peak monthly and weekly base load electricity futures, and slightly less monthly base load futures. As CHP decreases the microgrid's CVaR on its own, the scope for CVaR reduction from electricity futures is much lower. The microgrid purchases only monthly electricity base load futures in considerable amount since, as Fig. 3.14 indicates, these futures can be used the most efficiently to reduce the microgrid's CVaR when the 600 kW_e CHP unit is not enough to meet all electricity demand. Still, the share of electricity futures is much lower compared to the one of the microgrid with no on-site generation and microgrid with MT, thereby indicating that on-site generation with CHP and electricity futures are substitutes. As a result of the high share of on-site generation, on average 64.6% of the microgrid's heat consumption is met through heat recovery. In the most risk-averse regime at $B = 10$, the microgrid's CVaR reduction amounts to €4.1k which is 5.9% of the CVaR at the risk-neutral regime at $B = 0$. This is slightly higher in relative terms than the maximum CVaR reduction in a microgrid with no on-site generation, which indicates that gas futures are more efficient in reducing CVaR when used with CHP.

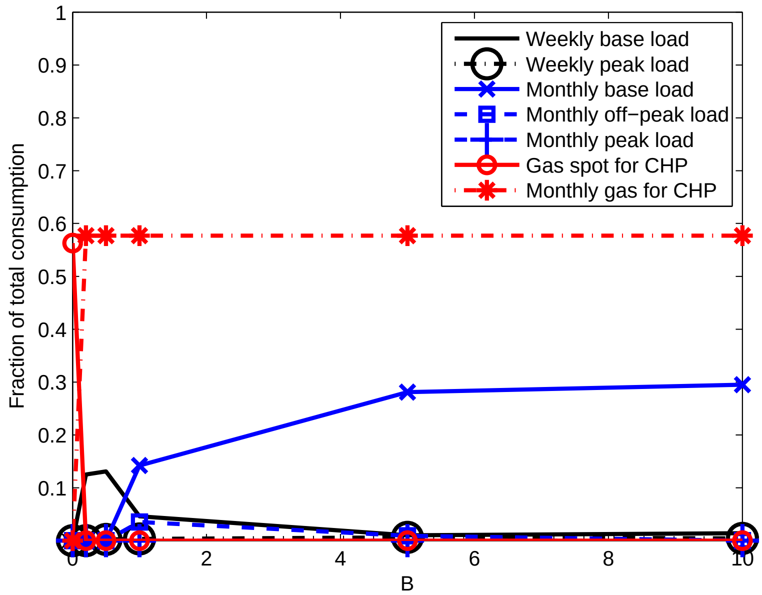


Figure 3.17: Electricity Consumption with CHP

3.6 Conclusions

With growing demand for cheap and reliable electricity, microgrids are likely to play a vital role in the future energy industry. In accordance with previous studies, our results show that a microgrid with an installed CHP unit can, indeed, contribute to energy savings and lower CO_2 emissions. To encourage customer adoption, numerous initiatives and subsidy schemes have been introduced by the EU and its member states. However, the development of the microgrid and CHP sectors have been slower than expected. One of the possible reasons for this is the financial uncertainty associated with operating on-site generation due to deregulated energy markets.

We present a multi-stage mean-risk stochastic optimisation model that can be used to reduce a microgrid's operational risk exposure through on-site generation and electricity and gas futures purchases. By applying this model to a hypothetical hospital, we find that on-site generation, either with MT or with CHP, can reduce the expected operational cost of energy procurement. However, the reduction in expected cost with MT without heat recovery is minimal, and the microgrid's CVaR relative to its expected cost is larger than without on-site generation. This is in contrast to the results in Chapter 2, where we find that on-site generation without heat recovery can function also as a physical hedge, i.e., it can reduce the variability of the microgrid's expected cost. As the decision time periods are much longer in the previous technology selection model than in the operational model, i.e., 2190 hours compared to 12 hours, this indicates that an MT unit, because of its low efficiency, cannot exploit the difference in gas and electricity prices when it is sustained for only a short period. In contrast, a microgrid with CHP can lower its expected cost significantly, on average 8.7-fold more than MT, and can reduce the microgrid's CVaR both in absolute terms and relative to its expected cost. This supports our findings in Chapter 2, and confirms the value of CHP as a physical hedge. Furthermore, when the microgrid has access to futures markets, we find that monthly gas futures and on-site generation with CHP exhibit complementarity, i.e., the presence of gas futures increases the demand of a risk-averse microgrid for on-site generation. Therefore, improving gas futures market liquidity can contribute to customer adoption of DG and, hence, it can lead to more sustainable electricity generation. On the other hand, we find that electricity futures are substitutes for on-site generation. Nevertheless, both the microgrid's attributes as a physical hedge and its interaction with gas futures can be utilised only with a stochastic programming model. Thus, in contrast to the extant literature, we provide a risk-management strategy for improving the viability of CHP as well as policy insights regarding access to liquid futures markets.

Chapter 4

Transmission and Wind Investment in a Deregulated Electricity Industry

4.1 Introduction

4.1.1 Background

Restructuring of the electric power industry was precipitated by the belief that the regulated paradigm would not meet growing demand efficiently (Hyman, 2010). As the functions of the industry such as generation, distribution, and retailing could be handled together by an investor-owned utility (IOU) with transmission planning and reliability under the auspices of a system operator, there was little incentive to develop new technologies for the market when profits were regulated. At the same time, since a single IOU operated in each area and prices were merely set administratively, there was no need for either risk management or strategic analysis. Although a plethora of post-restructuring market designs have emerged (Wilson, 2002), they have generally required incumbent IOUs to divest their generation assets with transmission and distribution remaining regulated. Consequently, these reforms have introduced endogenous price formation and imperfect competition, which necessitate a strategic view of decision making (Hobbs, 1995; Helman, 2004). Moreover, market-driven transmission investment has been proposed by the US FERC's July 2002 Standard Market Design (SMD) and the EU's Regulation EC 1228/2003 (Commission of the European Communities, 2003).

Recently, sustainability issues have entered the policy debate. Several governments are committed to CO_2 emissions targets in order to mitigate the effects of climate change, e.g., the EU's aim of 20-20-20 by 2020 (Communication from the European Commission, 2014). The policymaking dilemma is to forge a delicate balance between achieving the targets while not interfering with industry. Ironically, relative to the centralised paradigm, policymakers have ceded more control to industry while simultaneously having set loftier goals in terms of economic efficiency and environmental sustainability. Since much of the transition to a sustainable energy system will rely on wind as a lynchpin technology, aspects of wind such as intermittency, non-dispatchability, and remoteness mean that policymakers will need to consider concomitant transmission expansion when devising measures to encourage wind investment (Kunz, 2013). Consequently, policymakers require a deeper understanding of how market designs interact with strategic behaviour in delivering outcomes.

4.1.2 Literature Review

Under regulation, conventional least-cost methods could be employed to determine optimal transmission and generation investment (Hobbs, 1995). However, with deregulation, transmission and generation investment are made by separate entities with distinct and often conflicting incentives. For example, regulated transmission system operators (TSOs) seek to maximise social welfare, while power companies are interested in profit maximisation. In order to handle such game-theoretic interactions, complementarity modelling has been proposed to find Nash equilibria, i.e., solutions from which no agent has a unilateral incentive to deviate (Gabriel et al., 2012; Ruiz et al., 2014). Furthermore, complementarity modelling is amenable for analysing strategic behaviour in deregulated electricity industries due to its accommodation of physical features of the power system, i.e., Kirchoff's laws and intermittent generation (Hobbs, 2001).

The interaction of market agents maximising their objective functions results in an equilibrium problem. Since for linear and convex non-linear programs the Karush-Kuhn-Tucker (KKT) optimality conditions are both necessary and sufficient (Gabriel et al., 2012), the solution to agents' problems are equivalent to solutions of the corresponding complementarity problem (Fig. 4.1). Bi-level models are particularly relevant for policy analysis of the strategic interactions that arise when a dominant (leader) agent influences equilibrium prices by anticipating the decisions of followers at the lower level. Effectively, the leader's optimisation problem is constrained by a set of optimisation problems and equilibrium constraints at the lower level. If each lower-level problem is convex, then it may be replaced by its KKT conditions, thereby re-formulating the bi-level problem as a mathematical program with equilibrium constraints (MPEC). Ruiz and Conejo (2009) address the optimal offering strategy of a dominant power company with endogeneity in the objective function, i.e., the income of the power company is the product of the generation level and the equilibrium demand, which in turn depends on the generation level. Consequently, this results in an MPEC with non-linear objective function which tends to be difficult to solve (Bussieck and Vigerske, 2010). Ruiz and Conejo (2009) demonstrate that such problems may be resolved by using strong duality (Bertsekas, 1999) to render the problem as a MILP and to treat complementarity conditions via disjunctive constraints (Fortuny-Amat and McCarl, 1981). An alternative approach is presented in Wogrin et al.

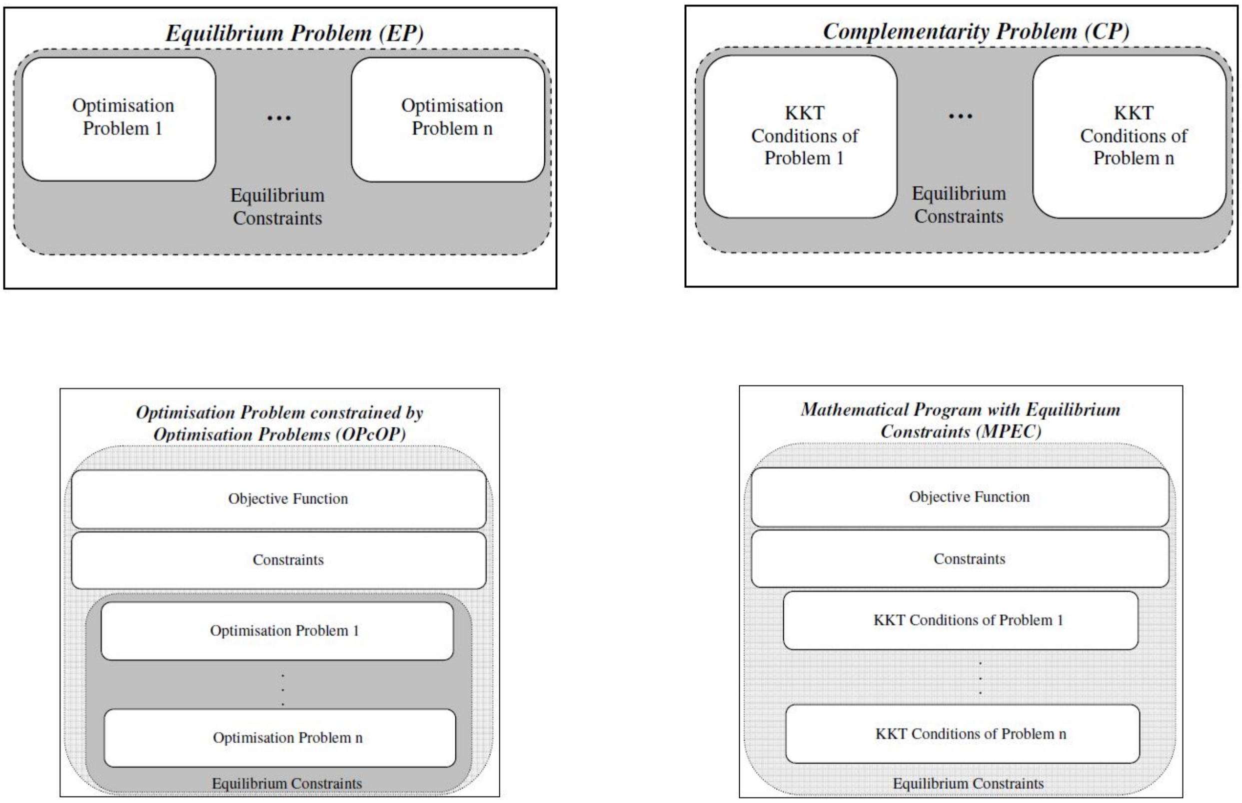


Figure 4.1: Equilibrium Problems and Their Re-Formulations

(2011) where the endogeneity in the MPEC's objective function is re-formulated through bi-linear expansion.

Closer to our effort are Garcés et al. (2009) with a welfare-maximising TSO at the upper level making transmission investment constrained by market clearing at the lower levels and Baringo and Conejo (2012) with a cost-minimising TSO at the upper level making both transmission and wind investment decisions constrained by market-clearing decisions of producers at the lower level(s). In contrast to Burke and O'Malley (2010) that assume a fixed transmission network, Baringo and Conejo (2012) illustrate the need to consider transmission and wind jointly. Still within a bi-level framework, Wogrin et al. (2013) use the framework of Kreps and Scheinkman (1983) to investigate a two-stage duopoly in which producers make investment decisions in the first stage and operational ones in the second stage. Within multi-stage games, Fudenberg and Tirole (1991) distinguish closed-loop and open-loop information structures. A game corresponds to the closed-loop information structure if participants can condition their decisions at any given stage on all the decisions made up until that stage. Conversely, in a game with an open-loop information structure, the history of play does not have any effect on the participants' decisions, which depend only on the corresponding time period. Wogrin et al. (2013) find that a closed-loop bi-level equilibrium problem with equilibrium constraints (EPEC) yields the same result as an open-loop mixed-complementarity problem (MCP) for any conjectural variation in the spot market as long as there is a single load period and the spot market is at least as competitive as in the Cournot case. This justifies a single-level approximation of the producers' bi-level problem. Such an equivalence may still hold when there are multiple load periods as demonstrated by an example from Wogrin et al. (2013). However, at the same time, Wogrin et al. (2013) present a counter-example in which the installed capacity is actually lower in the closed-loop (EPEC) model relative to the open-loop (MCP) model when spot markets are closer to being perfectly competitive, thereby indicating that open-loop results may not always generalise for multiple time periods. Moving on to a tri-level model, Sauma and Oren (2006, 2007) have a welfare-maximising TSO at the upper level making transmission investments, producers at the middle level making generation capacity investments, and market clearing at the lower level. Thus, this is a more complicated problem than even an EPEC, but Sauma and Oren (2006, 2007) do not attempt to solve it directly. Rather, they compare pre-determined transmission investment proposals from the perspective of various planners. In contrast to Sauma and Oren (2006), Sauma and Oren (2007) focus on market power by the producers and note that diverging objectives for the TSO may lead to politically infeasible investment plans.

Although transmission expansion has largely remained under the control of regulated TSOs, market-based models for transmission investment have been proposed in both the UK and the US. For example, Hogan (1992) posits a role for a merchant investor (MI) who would build new transmission lines motivated by the collection of congestion rents between grid nodes. However, the efficient outcomes hypothesised by Hogan (1992) under the MI are subverted if market power exists (Joskow and Tirole, 2005). In discussing the landscape for merchant transmission investment in Europe, Kristiansen and Rosellón (2010) note that financial transmission rights (FTRs) would be beneficial for dealing with externalities and providing hedging capabilities for investors. Yet, empirical analyses of markets for FTRs in the US have shown inefficiencies, e.g., divergent forward and spot prices for congestion rents, to exist in their operations, especially in congested regions (Bartholomew et al., 2003).

4.1.3 Research Objectives and Contribution

Given this background, we aim to gain policy insights into market design by analysing transmission and wind investment by distinct agents reflecting strategic behaviour: at the upper level, we posit that a TSO or an MI invests in new transmission lines (acting as a Stackelberg leader), while at the lower level, profit-maximising conventional and wind producers make investment and operational decisions with transmission flows governed by the relevant grid owner. In contrast to Baringo and Conejo (2012), we allow for market power at the lower level and find that this specification of industry (as behaving either perfectly competitively or à la Cournot) affects both lower- and upper-level decisions.

Moreover, unlike the extant literature, we investigate the implications of transmission investment made by an MI in a bi-level model. Finally, similarly to Tanaka and Chen (2013), we explore the impact of a policy measure such as the renewable portfolio standard (RPS). In this type of scheme, producers are required to supply a certain percentage of electricity from renewables to meet the quota set by the government (Kovacevic et al., 2013). They can either generate electricity from renewable sources for which they receive renewable energy certificate (REC) on a pro rata basis, or they can comply with the regulation by purchasing the required amount of RECs. As RECs are traded on a separate certificate market, theoretically, such regulation leads to efficient outcomes (Haas et al., 2011). A similar scheme is the cap-and-trade mechanism for emissions, which could also be investigated using our approach (Limpaitoon et al., 2014). In a cap-and-trade system, a limit is set on the total amount of greenhouse gases that can be emitted by specified sectors in a given year. Within the cap, companies receive emission allowances that they can trade with one another as needed. To avoid severe fines, at the end of year, each participating company must possess enough allowances to cover its greenhouse emissions it released.

We demonstrate that results are largely intuitive if producers at the lower level are price takers: generation capacity is added by the least costly producers, the conventional producer at the node with the highest demand does not face competition, and power flows from the less costly wind producer to the node with more capital-intensive (wind) producers. The impact of having the TSO or the MI at the upper level affects mainly the magnitudes of the outcomes and not their fundamental compositions. Under a lower-level industry behaving as a Cournot oligopoly, however, regardless of the market design (TSO or MI), a greater fraction of generation comes from wind because producers withhold capacity. Their exercise of market power causes a welfare-maximising TSO to subsidise wind to boost consumer surplus and a profit-maximising MI to build more transmission lines in order to encourage more transmission flow. The somewhat counterintuitive result under a Cournot oligopoly leads to power flow from a wind producer to the node where a conventional producer was the sole incumbent. Finally, by implementing an RPS constraint requiring a given percentage of energy to be provided by renewable sources, we examine how the renewable-boosting outcome of the oligopoly may be attained even under perfect competition.

4.2 Problem Formulation

4.2.1 Nomenclature

Indices and Sets

$i \in \mathcal{I}$: power producers
$\mathcal{I}^{\mathrm{c}} \subseteq \mathcal{I}$: conventional power producers
$\mathcal{I}^{\mathrm{w}} \subseteq \mathcal{I}$: wind power producers
$n \in \mathcal{N}$: grid nodes
n_ℓ^+: node index for starting node of line ℓ
n_ℓ^-: node index for ending node of line ℓ
$\ell \in \mathcal{L}$: transmission lines
$j \in \mathcal{J}_\ell$: discrete capacity level of transmission investment on line ℓ (including the existing level, j_0)
$\mathcal{L}_n^+$: set of lines starting at node n
$\mathcal{L}_n^-$: set of lines ending at node n
$t \in \mathcal{T}$: time periods
$s \in \mathcal{S}$: scenarios

Parameters

$C_{\ell,j}^{arc}$: amortised expansion cost (including for the existing level, $C_{\ell,j_0}^{arc} = 0$) of line ℓ with capacity level j (€/MW)
$K_{\ell,j}^{arc}$: transmission capacity (including for the existing level, K_{ℓ,j_0}^{arc}) of line ℓ with capacity level j (MW)
$B_{\ell,j}$: network susceptance of line ℓ with capacity level j ($1/\Omega$)
$S_n \in \{0,1\}$: dummy parameter for slack node (–)
A_n^{int}: intercept of the inverse demand curve at node n (€/MW)
A_n^{slp}: slope of the inverse demand curve at node n (€/MW^2)
$\Theta_{i',i,n}$: conjectured response of producer i' on the change in sales by producer i at node n (–)
$C_{n,i}^{inv}$: amortised investment cost of producer i at node n (€/MW)
$C_{n,i}^{prod}$: generation cost of producer i at node n (€/MW)
$K_{n,i}^{prod}$: initial generation capacity of producer i at node n (MW)
$E_{n,t,s}$: availability factor for wind generation at node n in period t for scenario s (–)
P_s: probability of scenario s (–)
R: renewable portfolio standard (RPS) requirement (%)

Primal Variables

$d_{n,t,s}$: voltage angle at node n in period t for scenario s (rad)

$u_{\ell,j}$: transmission investment in capacity level j for line ℓ (MW)

$f_{\ell,j,t,s}$: realised flow on line ℓ at capacity level j in period t for scenario s (MW)

$\hat{f}_{\ell,t,s}$: realised flow on line ℓ in period t for scenario s (MW)

$g^{inv}_{n,i}$: generation capacity investment at node n by producer i (MW)

$q^{prod}_{n,i,t,s}$: generation at node n by producer i in period t for scenario s (MW)

$q^{sell}_{n,i,t,s}$: sales at node n by producer i in period t for scenario s (MW)

$p_{n,t,s}$: electricity price at node n in period t for scenario s (€/MW)

Dual Variables

$\mu^{+}_{\ell,j,t,s}, \mu^{-}_{\ell,j,t,s}$: shadow price on capacity for transmission line ℓ at capacity level j in period t for scenario s (€/MW)

$\psi_{\ell,j,t,s}$: shadow price on electricity flow on line ℓ at capacity level j in period t for scenario s (€/MW)

$\kappa_{\ell,t,s}$: shadow price on electricity flow on line ℓ in period t for scenario s (€/MW)

$\tau_{n,t,s}$: congestion fee at node n in period t for scenario s (€/MW)

$\xi_{n,t,s}$: dual for slack node n in period t for scenario s (–)

$\lambda^{\mathrm{c}}_{n,i,t,s}, \lambda^{\mathrm{w}}_{n,i,t,s}$: shadow price on generation capacity at node n for producer i in period t for scenario s (€/MW)

$\theta_{i,t,s}$: shadow price on energy balance for producer i in period t for scenario s (€/MW)

$\upsilon_{t,s}$: renewable energy certificate (REC) price in period t for scenario s (€/MW)

4.2.2 Assumptions

We assume that transmission capacity expansion can be made in discrete levels, $j \in \mathcal{J}_\ell$, for each line $\ell \in \mathcal{L}$ of the network. The susceptance of a line, $B_{\ell,j}$, and, thus, the power flow, $f_{\ell,j,t,s}$, depend on the chosen capacity level. Following Baringo and Conejo (2012), we use a DC load-flow approximation for network power flows, which is an acceptable convention in power systems economics as long as voltage angle differences are small, and assume that the realised power flow on line ℓ for capacity level j in period t and scenario s is proportional to the susceptance and voltage angle difference, i.e., $f_{\ell,j,t,s} = u_{\ell,j} B_{\ell,j}(d_{n^+_\ell,t,s} - d_{n^-_\ell,t,s}),\ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell$. If capacity level j is for line ℓ, then $u_{\ell,j} = 1$ with $f_{\ell,j,t,s}$ being positive or negative, depending on the direction of the flow. Furthermore, for $j' \in \mathcal{J}_\ell \setminus \{j\}$, $u_{\ell,j'} = 0$ such that $f_{\ell,j',t,s} = 0$ without any artificial constraints on the voltage angles. Thus, the realised flow on line ℓ can be computed as $\hat{f}_{\ell,t,s} = \sum_{j \in \mathcal{J}_\ell} f_{\ell,j,t,s},\ \forall \ell, t, s$. As a result, the net imports at node n are $\sum_{\ell \in \mathcal{L}^-_n} \hat{f}_{\ell,t,s} - \sum_{\ell \in \mathcal{L}^+_n} \hat{f}_{\ell,t,s}$.

Each producer is either conventional (using fossil fuel) or wind. Conventional producers, $i \in \mathcal{I}^{\mathrm{c}}$, have linear cost functions, while wind producers, $i \in \mathcal{I}^{\mathrm{w}}$, do not incur operational costs. In addition, conventional producers can decide how much to generate, whereas wind output is variable and non-dispatchable, i.e., determined by the availability factors $E_{n,t,s}$. Such variability in wind output may be due to differing wind potentials at various locations and uncertainty in future efficiency improvements of the technology. Other sources of variability, such as demand uncertainty, river inflows, and plant outages, likewise, drive investment decisions. However, whereas power companies may have years of experience in forecasting these sources, this may not be the case for the future availability of wind. Moreover, with the expected growth in renewables, wind power may account for a substantial share of variability in a future power system, and we take this as our main focus while acknowledging that it is not the only driver of investment. Meanwhile, since market rules like priority of wind production limit curtailment except in extreme situations, we assume wind to be non-dispatchable. Nevertheless, our model can easily be adapted to incorporate the dispatch of wind production. We account for variability in wind output by assuming a known and discrete distribution described by a number of scenarios capturing the wind availability factors ($E_{n,t,s}$) and their probabilities (P_s).

While any producer can install capacity at any node and sell electricity generated elsewhere by accessing transmission capacity, most power companies are well diversified and may own a portfolio of both conventional and wind plants. However, specialisation also leads firms to concentrate on particular technologies, e.g., Limpaitoon et al. (2014) report that the largest two firms in California have proportionately less conventional generation than the others as part of their portfolios. Thus, it is appropriate to think of each producer in our model as being a composite producer of a particular type (either predominantly conventional or predominantly wind). We assume that each node n in our transmission grid has its own linear inverse demand, $p_{n,t,s} = A_n^{int} - A_n^{slp} \sum_{i \in \mathcal{I}} q_{n,i,t,s}^{sell}$, in each period t and scenario s, which depends on sales at the node by all producers in equilibrium. Depending on the market design, each producer is part of either a Cournot oligopoly or a perfectly competitive industry. The degree of market power is reflected by the conjectured price response, which is the first derivative of the inverse demand with respect to electricity sold by a given producer, i.e., $\frac{\partial p_{n,t,s}}{\partial q_{n,i,t,s}^{sell}} = -A_n^{slp}\left(1 + \sum_{i' \in \mathcal{I} \setminus \{i\}} \Theta_{i',i,n}\right), \forall n, i, t, s$, where $\Theta_{i',i,n} = \frac{\partial q_{n,i',t,s}^{sell}}{\partial q_{n,i,t,s}^{sell}}$ for $i' \in \mathcal{I} \setminus \{i\}$ and $\Theta_{i',i,n} = 1$ otherwise. Hence, we model perfect competition and Cournot oligopoly when $\sum_{i' \in \mathcal{I} \setminus \{i\}} \Theta_{i',i,n}$ equals -1 and 0, respectively.

We formulate the transmission-expansion problem of the MI as a bi-level problem: transmission investment decisions are made at an upper level by the MI in anticipation of subsequent investment in and operation of wind and conventional generation capacity by the producers, transmission flow decisions of the MI, and market clearing, all captured by a number of lower-level problems. Effectively, we have a dominant MI investing in transmission capacity with wind and conventional producers as followers. We do not consider competing MIs for three reasons. First, this would typically involve a third decision-making level for procurement of transmission investment rights, which would make the problem a tri-level one (Sauma and Oren, 2007) and, therefore, much more computationally challenging. Second, only a few entities have the expertise to carry out transmission projects, e.g., the BritNed DC cable between the UK and The Netherlands was constructed in 2011 as a joint venture formed by a private holding company involving the National Grid and TenneT. Third, we would like to compare the MI and TSO market designs, and introducing a third level with procurement auctions would preclude such an analysis.

To approximate the impact on generation expansion and operational planning, the producers' problems are single level. This leads to an open-loop problem (MCP) for the producers rather than a more complicated closed-loop one (EPEC). While treating the producers' problems over two levels may impact our results based on the findings of Wogrin et al. (2013), we feel justified in using an open-loop representation of the producers' problems because the discrepancy between open- and closed-loop models occurs only for departures from a Cournot setting. Indeed, the imperfectly competitive nature of most electricity spot markets implies that it is important to focus on the Cournot case, which is a central point of our paper and an issue that is relatively unaddressed in most hierarchical models of transmission investment. Although transmission and generation investment decisions are static, we allow for dynamic operational decisions and allocation of transmission capacity over time and scenarios. Thus, investment decisions are made in a first stage without anticipation of the wind output, whereas operational decisions are adapted to the realised scenario of availability factors, which leads to a two-stage stochastic program (Fig. 4.2). The stochastic bi-level problem can be re-formulated as an MPEC with equilibrium constraints obtained by deriving the optimality conditions for all lower-level problems. Since the lower level comprises convex optimisation problems, their KKT conditions are sufficient for optimality.

As benchmarks, we consider market designs with either a welfare-maximising central planner (CP) or a TSO. Since the CP mimics the regulated paradigm by controlling all aspects of the energy market, it solves a single-level stochastic problem covering transmission and generation investment as well as generation dispatch and transmission flows. Like the MI, the TSO has a bi-level stochastic programming problem with all decisions made as per the MI market design. The only difference is that the TSO maximises expected social welfare (SW) rather than expected profit from grid operations. Finally, in anticipation of forthcoming EU 2030 targets, we also run a numerical example with a stringent RPS target of 80%. This is plausible because the EU will require a 40% reduction in CO_2 emissions by 2030 relative to 1990 levels, which necessitates a deep decarbonisation of the power sector specifically due to foreseen electrification of the transport sector. Hitting

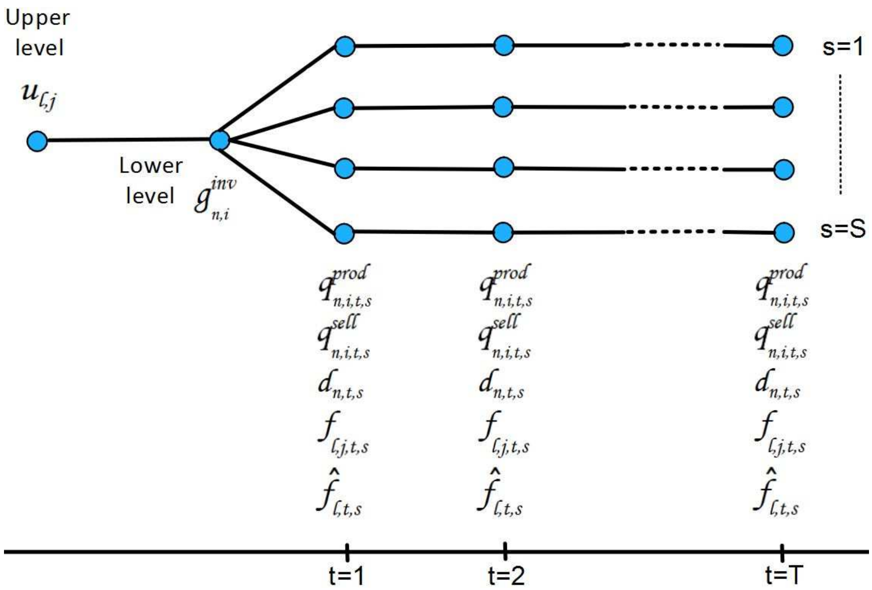


Figure 4.2: Decision-Making Levels

these targets will mean surmounting numerous technical challenges, but we are focused more on the implications of market design in such a transition assuming legally binding policy commitments.

4.2.3 Merchant Investor

MI's Upper-Level Problem

At the upper level, the MI decides on the transmission capacity level of a number of existing or potentially newly constructed transmission lines in order to maximise its expected profit given by the difference between grid congestion rents and investment costs:

$$\begin{aligned}\max_{\{u_{\ell,j}\}} \; & \sum_{s\in\mathcal{S}} P_s \sum_{t\in\mathcal{T}} \sum_{n\in\mathcal{N}} \tau_{n,t,s}\Big(\sum_{\ell\in\mathcal{L}_n^-} \hat{f}_{\ell,t,s} - \sum_{\ell\in\mathcal{L}_n^+} \hat{f}_{\ell,t,s}\Big) \\ & - \sum_{\ell\in\mathcal{L}} \sum_{j\in\mathcal{J}_\ell} C^{arc}_{\ell,j} u_{\ell,j} \end{aligned} \tag{4.1}$$

$$\text{s.t.} \;\; u_{\ell,j} \in \{0,1\}, \;\; \forall \ell, \forall j \in \mathcal{J}_\ell \tag{4.2}$$

$$\sum_{j\in\mathcal{J}_\ell} u_{\ell,j} = 1, \quad \forall \ell \tag{4.3}$$

Note that if $u_{\ell,j_0} = 1$, then existing capacity remains and no new capacity is constructed. We model congestion pricing by assuming that all power flows through a hub node of the network without generation and consumption (Hobbs, 2001). Thus, transmission flow between any two nodes is assumed to take place in two parts. The electricity flows from the injecting node to the hub node and then from the hub node to the receiving node. As we use a linearised DC approximation for network load flows, the choice of hub node is arbitrary, i.e., load flows resulting from a unit injection at one node and a unit withdrawal at another do not depend on the selected hub through which the transmission is routed. We further assume that the MI charges a node-dependent congestion fee, $\tau_{n,t,s}$, for transmitting power from this hub to each node. The shadow price on market-clearing condition (4.35) sets the congestion fee. Upper-level problem (4.1)-(4.3) is constrained by lower-level problems and equilibrium conditions.

MI's Lower-Level Problem

At the lower level, the MI determines flows on existing and newly constructed lines in order to maximise expected congestion rents:

$$\max_{\Gamma} \sum_{s\in\mathcal{S}} P_s \sum_{t\in\mathcal{T}} \sum_{n\in\mathcal{N}} \tau_{n,t,s}\Big(\sum_{\ell\in\mathcal{L}_n^-} \hat{f}_{\ell,t,s} - \sum_{\ell\in\mathcal{L}_n^+} \hat{f}_{\ell,t,s}\Big) \tag{4.4}$$

$$\text{s.t. } f_{\ell,j,t,s} = u_{\ell,j} B_{\ell,j}(d_{n_\ell^+,t,s} - d_{n_\ell^-,t,s}) \;\; (\psi_{\ell,j,t,s}),$$

$$\forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.5}$$

$$f_{\ell,j,t,s} \le K_{\ell,j}^{arc} \;\; (\mu_{\ell,j,t,s}^+), \;\; \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.6}$$

$$- f_{\ell,j,t,s} \le K_{\ell,j}^{arc} \;\; (\mu_{\ell,j,t,s}^-), \;\; \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.7}$$

$$\hat{f}_{\ell,t,s} = \sum_{j\in\mathcal{J}_\ell} f_{\ell,j,t,s} \;\; (\kappa_{\ell,t,s}), \;\; \forall \ell, t, s \tag{4.8}$$

$$S_n d_{n,t,s} = 0 \;\; (\xi_{n,t,s}), \;\; \forall n, t, s \tag{4.9}$$

$$d_{n,t,s} \text{ u.r.s.}, \;\; \forall n, t, s; \;\; f_{\ell,j,t,s} \text{ u.r.s.}, \;\; \forall \ell, t, s, \forall j \in \mathcal{J}_\ell,$$

$$\hat{f}_{\ell,t,s} \text{ u.r.s.}, \;\; \forall \ell, t, s \tag{4.10}$$

where $\Gamma = \{\hat{f}_{\ell,t,s}, f_{\ell,j,t,s}, d_{n,t,s}\}$ and u.r.s. denotes variables of unrestricted sign. Constraint (4.5) defines the flow on each line for each capacity level as a function of the difference in voltage angles, transmission capacity choice (fixed at the upper level), and line susceptance (Baringo and Conejo, 2012). The upper and lower limits on transmission flows for each capacity level of each line are set by (4.6) and (4.7), respectively, while (4.8) indicates the realised flow on each line. Restrictions (4.9) set the slack node for calculating voltage angles of the network. Moreover, the corresponding dual variables are in brackets.

The KKT conditions for the MI's lower-level problem are:

$$- P_s(\tau_{n_\ell^-,t,s} - \tau_{n_\ell^+,t,s}) + \kappa_{\ell,t,s} = 0 \text{ with } \hat{f}_{\ell,t,s} \text{ u.r.s.},$$

$$\forall \ell, t, s \tag{4.11}$$

$$\psi_{\ell,j,t,s} + \mu^{+}_{\ell,j,t,s} - \mu^{-}_{\ell,j,t,s} - \kappa_{\ell,t,s} = 0 \text{ with } f_{\ell,j,t,s} \text{ u.r.s.},$$

$$\forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.12}$$

$$-\sum_{\ell \in \mathcal{L}^{+}_{n}} \sum_{j \in \mathcal{J}_\ell} u_{\ell,j} B_{\ell,j} \psi_{\ell,j,t,s} + \sum_{\ell \in \mathcal{L}^{-}_{n}} \sum_{j \in \mathcal{J}_\ell} u_{\ell,j} B_{\ell,j} \psi_{\ell,j,t,s}$$

$$+ S_n \xi_{n,t,s} = 0 \text{ with } d_{n,t,s} \text{ u.r.s.}, \ \forall n, t, s \tag{4.13}$$

$$f_{\ell,j,t,s} - u_{\ell,j} B_{\ell,j} (d_{n^{+}_{\ell},t,s} - d_{n^{-}_{\ell},t,s}) = 0$$

$$\text{with } \psi_{\ell,j,t,s} \text{ u.r.s.}, \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.14}$$

$$0 \leq K^{arc}_{\ell,j} - f_{\ell,j,t,s} \perp \mu^{+}_{\ell,j,t,s} \geq 0, \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.15}$$

$$0 \leq K^{arc}_{\ell,j} + f_{\ell,j,t,s} \perp \mu^{-}_{\ell,j,t,s} \geq 0, \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.16}$$

$$\hat{f}_{\ell,t,s} - \sum_{j \in \mathcal{J}_\ell} f_{\ell,j,t,s} = 0 \text{ with } \kappa_{\ell,t,s} \text{ u.r.s.}, \ \forall \ell, t, s \tag{4.17}$$

$$S_n d_{n,t,s} = 0 \text{ with } \xi_{n,t,s} \text{ u.r.s.}, \ \forall n, t, s \tag{4.18}$$

Producers' Lower-Level Problems

Each conventional producer $i \in \mathcal{I}^{c}$ decides on investment and operation of generating units by maximising expected profit. This is revenue minus congestion rent, operating cost, compliance cost with the RPS stemming from renewable energy certificates (RECs), and investment cost:

$$\begin{aligned} \max_{\Gamma_i} \ & \sum_{s \in \mathcal{S}} P_s \sum_{t \in \mathcal{T}} \sum_{n \in \mathcal{N}} \Big(\big(A^{int}_{n} - A^{slp}_{n} \sum_{i' \in \mathcal{I}} q^{sell}_{n,i',t,s} \\ & - \tau_{n,t,s}\big) q^{sell}_{n,i,t,s} - (C^{prod}_{n,i} - \tau_{n,t,s} + R\upsilon_{t,s}) q^{prod}_{n,i,t,s} \Big) \\ & - \sum_{n \in \mathcal{N}} C^{inv}_{n,i} g^{inv}_{n,i} \end{aligned} \tag{4.19}$$

$$\text{s.t. } q^{prod}_{n,i,t,s} \leq K^{prod}_{n,i} + g^{inv}_{n,i} \ \ (\lambda^{c}_{n,i,t,s}), \ \forall n, t, s \tag{4.20}$$

$$\sum_{n \in \mathcal{N}} q^{prod}_{n,i,t,s} - \sum_{n \in \mathcal{N}} q^{sell}_{n,i,t,s} = 0 \ \ (\theta_{i,t,s}), \ \forall t, s \tag{4.21}$$

$$q^{prod}_{n,i,t,s} \geq 0, q^{sell}_{n,i,t,s} \geq 0, \ \forall n, t, s, \ \ g^{inv}_{n,i} \geq 0, \ \forall n \tag{4.22}$$

Here, $\Gamma_i = \{q^{prod}_{n,i,t,s}, q^{sell}_{n,i,t,s}, g^{inv}_{n,i}\}$. Congestion pricing implies that a producer receives a payment to send power from the generation node to the hub node, while it makes a payment to send power from the hub node to the sales node. Correspondingly, the cost of transmitting electricity from node n to node n' is $-\tau_{n,t,s} + \tau_{n',t,s}$. Since in our model every flow is routed through the hub node, this pricing method ensures that producers selling electricity at their local nodes do not pay for transmission as their payments and receipts cancel out. Also, note that the cost of transmission can be negative, which implies that the grid owner subsidises the the load flow. The transmission payments are again shadow prices from the market-clearing condition (4.35). The problem is subject to capacity constraints on production (4.20) and energy balance between total production and sales (4.21). Following Tanaka and Chen (2013), we account for the renewable energy credit (REC) payment via the exogenous RPS fraction, R, and the shadow price on the RPS constraint (4.36).

The KKT conditions for this problem are:

$$
\begin{aligned}
& 0 \leq -P_s\big(A_n^{int} - A_n^{slp}\big((1 + \sum_{i' \in \mathcal{I} \setminus \{i\}} \Theta_{i,i',n}) q_{n,i,t,s}^{sell} \\
& + \sum_{i' \in \mathcal{I}} q_{n,i',t,s}^{sell}\big) - \tau_{n,t,s}\big) + \theta_{i,t,s} \perp q_{n,i,t,s}^{sell} \geq 0, \forall n, t, s \qquad (4.23) \\
& 0 \leq P_s(C_{n,i}^{prod} - \tau_{n,t,s} + R \upsilon_{t,s}) + \lambda_{n,i,t,s}^{\mathrm{c}} - \theta_{i,t,s} \\
& \perp q_{n,i,t,s}^{prod} \geq 0, \forall n, t, s \qquad (4.24) \\
& 0 \leq C_{n,i}^{inv} - \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} \lambda_{n,i,t,s}^{\mathrm{c}} \perp g_{n,i}^{inv} \geq 0, \forall n \qquad (4.25) \\
& 0 \leq K_{n,i}^{prod} + g_{n,i}^{inv} - q_{n,i,t,s}^{prod} \perp \lambda_{n,i,t,s}^{\mathrm{c}} \geq 0, \forall n, t, s \qquad (4.26) \\
& \sum_{n \in \mathcal{N}} q_{n,i,t,s}^{prod} - \sum_{n \in \mathcal{N}} q_{n,i,t,s}^{sell} = 0 \text{ with } \theta_{i,t,s} \text{ u.r.s.}, \forall t, s \qquad (4.27)
\end{aligned}
$$

Each wind power producer $i \in \mathcal{I}^{\mathrm{w}}$ faces a similar problem:

$$
\begin{aligned}
\max_{\Gamma_i} \quad & \sum_{s \in \mathcal{S}} P_s \sum_{t \in \mathcal{T}} \sum_{n \in \mathcal{N}} \Big(\big(A_n^{int} - A_n^{slp} \sum_{i \in \mathcal{I}} q_{n,i,t,s}^{sell} \\
& - \tau_{n,t,s}\big) q_{n,i,t,s}^{sell} + (\tau_{n,t,s} + (1 - R)\upsilon_{t,s}) q_{n,i,t,s}^{prod} \Big) \\
& - \sum_{n \in \mathcal{N}} C_{n,i}^{inv} g_{n,i}^{inv} \qquad (4.28) \\
\text{s.t.} \quad & q_{n,i,t,s}^{prod} = E_{n,t,s}(K_{n,i}^{prod} + g_{n,i}^{inv}) \ \ (\lambda_{n,i,t,s}^{\mathrm{w}}), \\
& \forall n, t, s \qquad (4.29) \\
& \sum_{n \in \mathcal{N}} q_{n,i,t,s}^{prod} - \sum_{n \in \mathcal{N}} q_{n,i,t,s}^{sell} = 0 \ \ (\theta_{i,t,s}), \ \ \forall t, s \qquad (4.30) \\
& q_{n,i,t,s}^{prod} \geq 0, q_{n,i,t,s}^{sell} \geq 0, \ \ \forall n, t, s, \ \ g_{n,i}^{inv} \geq 0, \ \ \forall n \qquad (4.31)
\end{aligned}
$$

Note that in the objective function production costs of wind power production are assumed to be negligible and REC payments are replaced by earnings from RECs. Furthermore, the constraint (4.20) is replaced by (4.29) to reflect the non-dispatchable nature of wind.

The corresponding KKT conditions are:

$$(4.23), (4.27)$$

$$0 \leq -P_s(\tau_{n,t,s} + (1-R)\upsilon_{t,s}) + \lambda^{\mathrm{w}}_{n,i,t,s} - \theta_{i,t,s}$$

$$\perp q^{prod}_{n,i,t,s} \geq 0, \forall n, t, s \tag{4.32}$$

$$0 \leq C^{inv}_{n,i} - \sum_{s\in\mathcal{S}} \sum_{t\in\mathcal{T}} \lambda^{\mathrm{w}}_{n,i,t,s} E_{n,t,s} \perp g^{inv}_{n,i} \geq 0, \forall n \tag{4.33}$$

$$q^{prod}_{n,i,t,s} - E_{n,t,s}\left(K^{prod}_{n,i} + g^{inv}_{n,i}\right) = 0 \text{ with } \lambda^{\mathrm{w}}_{n,i,t,s} \text{ u.r.s.},$$

$$\forall n, t, s \forall t, s \tag{4.34}$$

Equilibrium Conditions

Market-clearing conditions stipulate that the transmission flow supplied by the grid owner to node n equals the producers' demand for transmission capacity, which they require in order to sell electricity at this node:

$$\sum_{i\in\mathcal{I}} q^{sell}_{n,i,t,s} - \sum_{i\in\mathcal{I}} q^{prod}_{n,i,t,s} + \sum_{\ell\in\mathcal{L}^+_n} \hat{f}_{\ell,t,s} - \sum_{\ell\in\mathcal{L}^-_n} \hat{f}_{\ell,t,s} = 0,$$

$$\text{with } \tau_{n,t,s} \text{ u.r.s.}, \ \forall n, t, s \tag{4.35}$$

The RPS constraint requires that share of wind power production from the total production is at least R:

$$0 \leq \sum_{n\in\mathcal{N}} \sum_{i\in\mathcal{I}^{\mathrm{w}}} q^{prod}_{n,i,t,s} - R \sum_{n\in\mathcal{N}} \sum_{i\in\mathcal{I}} q^{prod}_{n,i,t,s} \perp \upsilon_{t,s} \geq 0,$$

$$\forall t, s \tag{4.36}$$

MI's MPEC Formulation

The MI's MPEC is:

$$\begin{aligned}
\max_{\{u_{\ell,j}\}\cup\Gamma\cup\Gamma_i\cup\Xi^{MI}} \quad & (4.1)\\
\text{s.t.} \quad & (4.2)-(4.3); (4.11)-(4.18); (4.23), (4.27) \ \ \forall i \in \mathcal{I};\\
& (4.24)-(4.26) \ \ \forall i \in \mathcal{I}^{\mathrm{c}}; (4.32)-(4.34) \ \ \forall i \in \mathcal{I}^{\mathrm{w}};\\
& (4.35)-(4.36)
\end{aligned}$$

where $\Xi^{MI} = \{\mu^{+}_{\ell,j,t,s}, \mu^{-}_{\ell,j,t,s}, \psi_{\ell,j,t,s}, \kappa_{\ell,t,s}, \xi_{n,t,s}, \lambda^{\mathrm{c}}_{n,i,t,s}, \lambda^{\mathrm{w}}_{n,i,t,s}, \theta_{i,t,s}, \tau_{n,t,s}, \upsilon_{t,s}\}$ are lower-level dual variables.

4.2.4 Transmission System Operator

At the upper level, the TSO decides on transmission capacity such as to maximise expected social welfare. To determine the social welfare, we calculate first the consumers' surplus by integrating the inverse demand function from zero demand to the equilibrium demand. The social welfare is then given by subtracting the producers' variable and investment costs as well as the cost of grid expansion from the consumers' surplus:

$$\begin{aligned}
\max_{\{u_{\ell,j}\}} \quad & \sum_{s\in\mathcal{S}} P_s \sum_{t\in\mathcal{T}} \Big(\sum_{n\in\mathcal{N}} \big(A^{int}_n \sum_{i\in\mathcal{I}} q^{sell}_{n,i,t,s}\\
& - \frac{1}{2} A^{slp}_n \big(\sum_{i\in\mathcal{I}} q^{sell}_{n,i,t,s} \big)^2 \big) - \sum_{i\in\mathcal{I}^{\mathrm{c}}} \sum_{n\in\mathcal{N}} C^{prod}_{n,i} q^{prod}_{n,i,t,s} \Big)\\
& - \sum_{i\in\mathcal{I}} \sum_{n\in\mathcal{N}} C^{inv}_{n,i} g^{inv}_{n,i} - \sum_{\ell\in\mathcal{L}} \sum_{j\in\mathcal{J}_\ell} C^{arc}_{\ell,j} u_{\ell,j} \qquad (4.37)\\
\text{s.t.} \quad & (4.2)-(4.3)
\end{aligned}$$

At the lower level, the TSO enforces network feasibility constraints, i.e., load power flows are determined by voltage angle differences and they cannot exceed line capacities, (4.5)-(4.10), in which $u_{\ell,j}$ is fixed at the upper level. Thus, the TSO's MPEC is:

$$\begin{aligned}
\max_{\{u_{\ell,j}\}\cup\Gamma\cup\Gamma_i\cup\Xi^{TSO}} \quad & (4.37)\\
\text{s.t.} \quad & (4.2)-(4.3); (4.5)-(4.10); (4.23), (4.27) \ \ \forall i \in \mathcal{I};\\
& (4.24)-(4.26) \ \ \forall i \in \mathcal{I}^{\mathrm{c}}; (4.32)-(4.34) \ \ \forall i \in \mathcal{I}^{\mathrm{w}};
\end{aligned}$$

$$(4.35) - (4.36)$$

where $\Xi^{TSO} = \{\lambda^{\mathrm{c}}_{n,i,t,s}, \lambda^{\mathrm{w}}_{n,i,t,s}, \theta_{i,t,s}, \tau_{n,t,s}, \upsilon_{t,s}\}$.

4.2.5 Central Planner

The CP's optimisation problem can be solved as stochastic mixed-integer non-linear programming (MINLP) problem. The non-linearity stems from constraint (4.5), which includes the product of two decision variables. The CP's MINLP is formulated as:

$$\begin{aligned}
\max_{\{u_{\ell,j}\}\cup\Gamma\cup\Gamma_i} \quad & (4.37) \\
\text{s.t.} \quad & (4.2) - (4.3); (4.5) - (4.10); (4.20) \;\; \forall i \in \mathcal{I}^{\mathrm{c}}; \\
& (4.21) - (4.22) \;\; \forall i \in \mathcal{I}; (4.29) \;\; \forall i \in \mathcal{I}^{\mathrm{w}}; (4.35); \\
& \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}^{\mathrm{w}}} q^{prod}_{n,i,t,s} \geq R \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}} q^{prod}_{n,i,t,s} \\
& \forall n, t, s \qquad (4.38)
\end{aligned}$$

4.3 Problem Re-Formulations

Since MPEC model formulations involve a large number of complementarity constraints, they are highly non-linear. Currently, solvers for such non-linear problems are experimental and cannot guarantee global optima (Rosenthal, 2014), i.e., MPEC solvers based on the reduced gradient method are likely to converge to a local optimum (Gabriel et al., 2012). The MI's MPEC formulation poses additional difficulties since its objective function is also non-linear due to endogeneity. The MI's income is the sum of the products of the transmission flow and the congestion fee on each line, however, the congestion fee itself depends on the flow determined by the MI. Nevertheless, these MPEC problems can be re-cast as MILPs or mixed-integer quadratic programs (MIQPs), which can be then solved with advanced branch-and-cut algorithms. While research on solving MINLP problems is further ahead (Lee and Leyffer, 2012), it is still a new field, and solving an MINLP, if it is possible at all, takes much longer than solving an MILP. Therefore, we re-formulate the CP's MINLP problem as well.

Thus, starting with the MI's MPEC formulation, we linearise its objective function by applying strong duality (Luenberger and Ye, 2008) from linear programming (LP) to its lower-level problem (4.4)-(4.10):

$$\sum_{s\in\mathcal{S}} P_s \sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}} \tau_{n,t,s}\Big(\sum_{\ell\in\mathcal{L}_n^-}\hat{f}_{\ell,t,s} - \sum_{\ell\in\mathcal{L}_n^+}\hat{f}_{\ell,t,s}\Big)$$
$$= \sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}}\sum_{\ell\in\mathcal{L}}\sum_{j\in\mathcal{J}_\ell} K^{arc}_{\ell,j}(\mu^+_{\ell,j,t,s} + \mu^-_{\ell,j,t,s})$$

Consequently, the non-linear part of the MI's objective function can be replaced by a linear expression to yield the following objective function:

$$\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}}\sum_{\ell\in\mathcal{L}}\sum_{j\in\mathcal{J}_\ell} K^{arc}_{\ell,j}(\mu^+_{\ell,j,t,s} + \mu^-_{\ell,j,t,s})$$
$$-\sum_{\ell\in\mathcal{L}}\sum_{j\in\mathcal{J}_\ell} C^{arc}_{\ell,j} u_{\ell,j} \tag{4.39}$$

For this to hold, the primal and dual solutions, $\hat{f}_{\ell,t,s}$, $\tau_{n,t,s}$, $\mu^+_{\ell,j,t,s}$, and $\mu^-_{\ell,j,t,s}$ must satisfy the KKT conditions of the MI's lower-level problem.

Next, the KKT conditions can be replaced by disjunctive constraints (Fortuny-Amat and McCarl, 1981). For the MI's lower-level problem, constraints (4.11)-(4.18) can be re-formulated as:

$$-P_s(\tau_{n_\ell^-,t,s} - \tau_{n_\ell^+,t,s}) + \kappa_{\ell,t,s} = 0, \forall \ell, t, s \tag{4.40}$$

$$\psi_{\ell,j,t,s} + \mu^+_{\ell,j,t,s} - \mu^-_{\ell,j,t,s} - \kappa_{\ell,t,s} = 0, \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.41}$$

$$-\sum_{\ell\in\mathcal{L}_n^+}\sum_{j\in\mathcal{J}_\ell} B_{\ell,j}(\psi_{\ell,j,t,s} - \psi^{aux}_{\ell,j,t,s}) + \sum_{\ell\in\mathcal{L}_n^-}\sum_{j\in\mathcal{J}_\ell} B_{\ell,j}(\psi_{\ell,j,t,s}$$
$$-\psi^{aux}_{\ell,j,t,s}) + S_n\xi_{n,t,s} = 0, \forall n, t, s \tag{4.42}$$

$$-u_{\ell,j}M^d \le \psi_{\ell,j,t,s} - \psi^{aux}_{\ell,j,t,s} \le u_{\ell,j}M^d,$$
$$\forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.43}$$

$$-(1-u_{\ell,j})M^d \le \psi^{aux}_{\ell,j,t,s} \le (1-u_{\ell,j})M^d,$$
$$\forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.44}$$

$$-K^{arc}_{\ell,j}u_{\ell,j} \le f_{\ell,j,t,s} \le K^{arc}_{\ell,j}u_{\ell,j}, \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.45}$$

$$-(1-u_{\ell,j})M^{flow} \le f_{\ell,j,t,s} - B_{\ell,j}(d_{n_\ell^+,t,s} - d_{n_\ell^-,t,s})$$
$$\le (1-u_{\ell,j})M^{flow}, \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.46}$$

$$0 \le K^{arc}_{\ell,j} - f_{\ell,j,t,s} \le M^{arc^+} w^{arc^+}_{\ell,j,t,s}, \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.47}$$

$$0 \le \mu^+_{\ell,j,t,s} \le M^{arc^+}(1 - w^{arc^+}_{\ell,j,t,s}), \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.48}$$

$$0 \le K^{arc}_{\ell,j} + f_{\ell,j,t,s} \le M^{arc^-} w^{arc^-}_{\ell,j,t,s}, \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.49}$$

$$0 \leq \mu^{-}_{\ell,j,t,s} \leq M^{arc^{-}}(1 - w^{arc^{-}}_{\ell,j,t,s}), \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell \tag{4.50}$$

$$\hat{f}_{\ell,t,s} - \sum_{j \in \mathcal{J}_\ell} f_{\ell,j,t,s} = 0 \ \ , \ \ \forall \ell, t, s \tag{4.51}$$

$$S_n d_{n,t,s} = 0, \ \ \forall n, t, s \tag{4.52}$$

$$u_{\ell,j} \in \{0,1\}, \ \ \forall \ell, \forall j \in \mathcal{J}_\ell, \ \ \hat{f}_{\ell,t,s} \ \text{u.r.s.}, \ \ \forall \ell, t, s$$

$$f_{\ell,j,t,s} \ \text{u.r.s.}, \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell, \ \ d_{n,t,s} \ \text{u.r.s.}, \ \ \forall n, t, s$$

$$\psi_{\ell,j,t,s} \ \text{u.r.s.}, \ \ \psi^{aux}_{\ell,j,t,s} \ \text{u.r.s.}, \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell$$

$$\kappa_{\ell,t,s} \ \text{u.r.s.}, \ \ \forall \ell, t, s, \ \ \xi_{n,t,s} \ \text{u.r.s.}, \ \ \forall n, t, s$$

$$w^{arc^{+}}_{\ell,j,t,s}, \in \{0,1\}, w^{arc^{-}}_{\ell,j,t,s} \in \{0,1\}, \ \ \forall \ell, t, s, \forall j \in \mathcal{J}_\ell$$

$$\tau_{n,t,s} \ \text{u.r.s.}, \ \ \forall n, t, s \tag{4.53}$$

For conventional producer $i \in \mathcal{I}^{\mathrm{c}}$, the KKT conditions (4.23)-(4.27) are re-formulated in the same manner:

$$0 \leq -P_s\big(A^{int}_n - A^{slp}_n\big((1 + \sum_{i' \in \mathcal{I} \setminus \{i\}} \Theta_{i,i',n})q^{sell}_{n,i,t,s}$$

$$+ \sum_{i' \in \mathcal{I}} q^{sell}_{n,i',t,s}\big) - \tau_{n,t,s}\big) + \theta_{i,t,s} \leq M^{sell} w^{sell}_{n,i,t,s},$$

$$\forall n, t, s \tag{4.54}$$

$$0 \leq q^{sell}_{n,i,t,s} \leq M^{sell}(1 - w^{sell}_{n,i,t,s}) \ \ \forall n, t, s \tag{4.55}$$

$$0 \leq P_s(C^{prod}_{n,i} - \tau_{n,t,s} + R\upsilon_{t,s}) + \lambda^{\mathrm{c}}_{n,i,t,s} - \theta_{i,t,s}$$

$$\leq M^{prod} w^{prod}_{n,i,t,s}, \ \ \forall n, t, s \tag{4.56}$$

$$0 \leq q^{prod}_{n,i,t,s} \leq M^{prod}(1 - w^{prod}_{n,i,t,s}), \ \ \forall n, t, s \tag{4.57}$$

$$0 \leq C^{inv}_{n,i} - \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} \lambda^{\mathrm{c}}_{n,i,t,s} \leq M^{inv} w^{inv}_{n,i}, \ \ \forall n \tag{4.58}$$

$$0 \leq g^{inv}_{n,i} \leq M^{inv}(1 - w^{inv}_{n,i}), \ \ \forall n \tag{4.59}$$

$$0 \leq K^{prod}_{n,i} + g^{inv}_{n,i} - q^{prod}_{n,i,t,s} \leq M^{\lambda^{\mathrm{c}}} w^{\lambda^{\mathrm{c}}}_{n,i,t,s}, \ \ \forall n, t, s \tag{4.60}$$

$$0 \leq \lambda^{\mathrm{c}}_{n,i,t,s} \leq M^{\lambda^{\mathrm{c}}}(1 - w^{\lambda^{\mathrm{c}}}_{n,i,t,s}), \ \ \forall n, t, s \tag{4.61}$$

$$\sum_{n \in \mathcal{N}} q^{prod}_{n,i,t,s} - \sum_{n \in \mathcal{N}} q^{sell}_{n,i,t,s} = 0, \ \ \forall n, t, s \tag{4.62}$$

$$\theta_{i,t,s} \ \text{u.r.s.}, \ \ \forall t, s \tag{4.63}$$

$$w^{prod}_{n,i,t,s}, w^{sell}_{n,i,t,s}, w^{\lambda^{c}}_{n,i,t,s} \in \{0,1\}, \;\; \forall n,t,s \tag{4.64}$$

$$w^{inv}_{n,i} \in \{0,1\}, \;\; \forall n \tag{4.65}$$

Analogously, for wind producer $i \in \mathcal{I}^{\mathrm{w}}$, the disjunctive constraints are the same as in (4.54)-(4.65) with the following replacements for (4.56), (4.58), (4.60), and (4.61), which correspond to (4.32)-(4.34):

$$0 \le -P_s(\tau_{n,t,s} + (1-R)\upsilon_{t,s}) + \lambda^{\mathrm{w}}_{n,i,t,s} - \theta_{i,t,s}$$

$$\le M^{prod} w^{prod}_{n,i,t,s}, \;\; \forall n,t,s \tag{4.66}$$

$$0 \le C^{inv}_{n,i} - \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} \lambda^{\mathrm{w}}_{n,i,t,s} E_{n,t,s} \le M^{inv} w^{inv}_{n,i}, \;\; \forall n \tag{4.67}$$

$$q^{prod}_{n,i,t,s} - E_{n,t,s}(K^{prod}_{n,i} + g^{inv}_{n,i}) = 0, \;\; \forall n,t,s \tag{4.68}$$

$$\lambda^{\mathrm{w}}_{n,i,t,s} \;\; \text{u.r.s.}, \;\; \forall n,t,s \tag{4.69}$$

Finally, the market-clearing and RPS constraints (4.35)-(4.36) become:

$$\sum_{i \in \mathcal{I}} q^{sell}_{n,i,t,s} - \sum_{i \in \mathcal{I}} q^{prod}_{n,i,t,s} + \sum_{\ell \in \mathcal{L}^{+}_{n}} \hat{f}_{\ell,t,s} - \sum_{\ell \in \mathcal{L}^{-}_{n}} \hat{f}_{\ell,t,s} = 0,$$

$$\forall n,t,s \tag{4.70}$$

$$0 \le \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}^{\mathrm{w}}} q^{prod}_{n,i,t,s} - R \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}} q^{prod}_{n,i,t,s} \le M^{\upsilon} w^{\upsilon}_{t,s},$$

$$\forall t,s \tag{4.71}$$

$$0 \le \upsilon_{t,s} \le M^{\upsilon}(1 - w^{\upsilon}_{t,s}), \;\; \forall t,s \tag{4.72}$$

$$\tau_{n,t,s} \;\; \text{u.r.s.}, \;\; \forall n,t,s \tag{4.73}$$

$$w^{\upsilon}_{t,s} \in \{0,1\}, \;\; \forall t,s \tag{4.74}$$

Hence, the MILP for the MI is:

$$\begin{aligned} &\max_{\{u_{\ell,j}\} \cup \Gamma \cup \Gamma_i \cup \Xi^{MI} \cup \Phi^{MI}} \;\; (4.39) \\ &\text{s.t.} \;\; (4.2)-(4.3); \;\; (4.40)-(4.53); \;\; (4.54)-(4.55), (4.57), (4.59), \\ &\quad (4.62)-(4.65) \;\; \forall i \in \mathcal{I}; \;\; (4.56), (4.58), (4.60), (4.61) \;\; \forall i \in \mathcal{I}^{\mathrm{c}}; \\ &\quad (4.66)-(4.69) \;\; \forall i \in \mathcal{I}^{\mathrm{w}}; \;\; (4.70)-(4.74) \end{aligned}$$

where $\Phi^{MI} = \{w^{prod}_{n,i,t,s}, w^{sell}_{n,i,t,s}, w^{inv}_{n,i}, w^{\lambda^{c}}_{n,i,t,s}, w^{\lambda^{w}}_{n,i,t,s}, w^{arc^{+}}_{\ell,j,t,s}, w^{arc^{-}}_{\ell,j,t,s}, w^{\upsilon}_{t,s}, \psi^{aux}_{\ell,j,t,s}\}$.

Since the TSO's objective function (4.37) is quadratic, we directly use disjunctive constraints to formulate its MPEC as an MIQP:

$$\begin{aligned}
&\max_{\{u_{\ell,j}\}\cup\Gamma\cup\Gamma_i\cup\Xi^{TSO}\cup\Phi^{TSO}} \quad (4.37)\\
&\text{s.t.}\ (4.2)-(4.3);\ \ (4.8)-(4.10);(4.45)-(4.46);(4.54)-(4.55),(4.57),(4.59),\\
&\quad (4.62)-(4.65)\ \ \forall i\in\mathcal{I};\ \ (4.56),(4.58),(4.60),(4.61)\ \ \forall i\in\mathcal{I}^{\mathrm{c}};\\
&\quad (4.66)-(4.69)\ \ \forall i\in\mathcal{I}^{\mathrm{w}};\ \ (4.70)-(4.74)\forall\ell,t,s,\forall j\in\mathcal{J}_\ell
\end{aligned}$$

where $\Phi^{TSO}=\{w^{prod}_{n,i,t,s},w^{sell}_{n,i,t,s},w^{inv}_{n,i},w^{\lambda^{\mathrm{c}}}_{n,i,t,s},w^{\lambda^{\mathrm{w}}}_{n,i,t,s},w^{v}_{t,s}\}$.

Likewise, the CP's MINLP may be re-formulated as an MIQP:

$$\begin{aligned}
&\max_{\{u_{\ell,j}\}\cup\Gamma\cup\Gamma_i} \quad (4.37)\\
&\qquad \text{s.t.}\ (4.2)-(4.3);(4.8)-(4.10);(4.20)\ \ \forall i\in\mathcal{I}^{\mathrm{c}};\\
&\qquad\quad (4.21)-(4.22)\ \ \forall i\in\mathcal{I};(4.29)\ \ \forall i\in\mathcal{I}^{\mathrm{w}};\\
&\qquad\quad (4.35);(4.38);(4.45)-(4.46)
\end{aligned}$$

4.4 Numerical Examples

4.4.1 Data

We implement the three market designs on a three-node network with two operating hours and scenarios (Fig. 4.3). The arrows indicate forward directions for the flows, i.e., the corresponding decision variable will have a positive (negative) sign if the realised flow is in the indicated (opposite) direction. All nodes are initially disconnected, but transmission lines with attributes given in Fig. 4.4 may be built. In the DC load-flow model, the ease with which current passes through a line is denoted by susceptance. In Fig. 4.4, we indicate the transmission capacity (susceptance) by the broken (solid) series measured on the left (right) axis. Specifically, we consider fifteen discrete capacity levels with corresponding susceptances. The susceptance of a line is determined by several factors, such as physical characteristics of the conductor, i.e., its length, cross-section area, and material composition, and it is affected also by conditions the line is used in, i.e., applied voltage, air temperature, and atmospheric pressure. Assuming typical values for aluminium conductors, we calculate the transmission capacities and susceptances based on Reta-Hernández (2012). Although in our example the network is initially disconnected, because we discretise the transmission capacity levels, we could easily implement an instance with positive

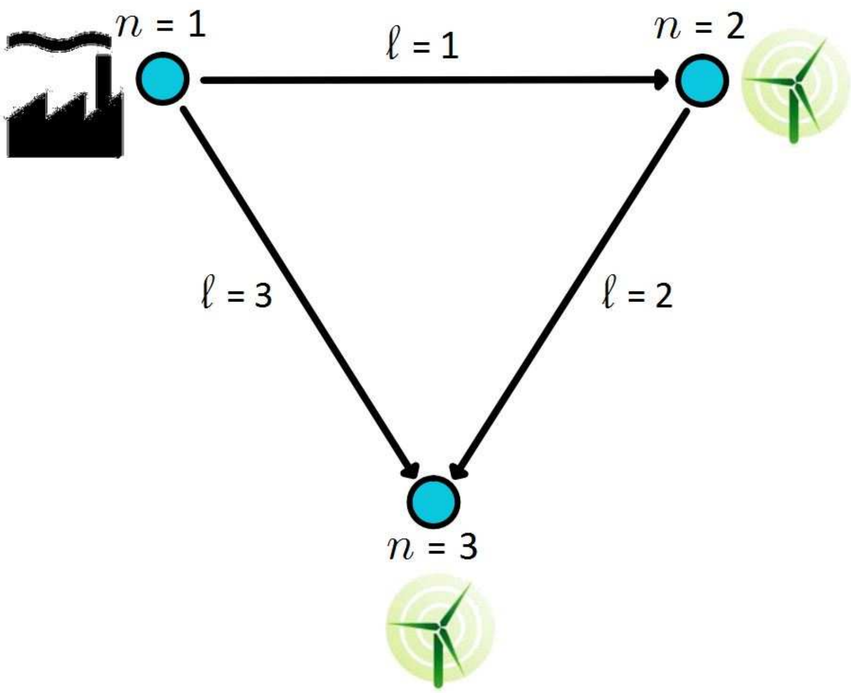


Figure 4.3: Transmission Network with Three Nodes

initial line capacities. Since we model representative hours, the transmission investment costs for lines of length 700 km are amortised on an hourly basis assuming a construction cost of \$1080/(MW-km), which is in line with Baringo and Conejo (2102). These costs range from €11.9/MW to €337/MW for 220 kV lines corresponding to capacities 3.7 MW to 103.7 MW, respectively. For generation, we use the US Energy Information Administration's 2014 Annual Energy Outlook to calculate operating costs and amortised capacity costs of conventional (\$2930/kW capital cost and 40% efficiency for coal) and wind plants (capital costs of \$2210/kW and \$6230/kW for onshore and offshore turbines, respectively). All amortisation assumes a lifetime of 20 years and an interest rate of 3% per annum. Finally, in Table 4.1, we assume that the demand centre is at node 1 (with an existing conventional plant), but potential wind resources are based at thinly populated locations (nodes 2 and 3).

Table 4.1: Demand and Production Parameters

Parameter	$n = 1$, $i = 1$	$n = 2$, $i = 2$	$n = 3$, $i = 3$
A_n^{int}	110	70	60
A_n^{slp}	1	1	1
$E_{n,s,1}$	0	0.30	0.45
$E_{n,1,2}$	0	0.33	0.50
$E_{n,2,2}$	0	0.27	0.41
$C_{n,i}^{inv}$	12.58	9.47	26.71
$C_{n,i}^{prod}$	21	0	0
$K_{n,i}^{prod}$	15	0	0

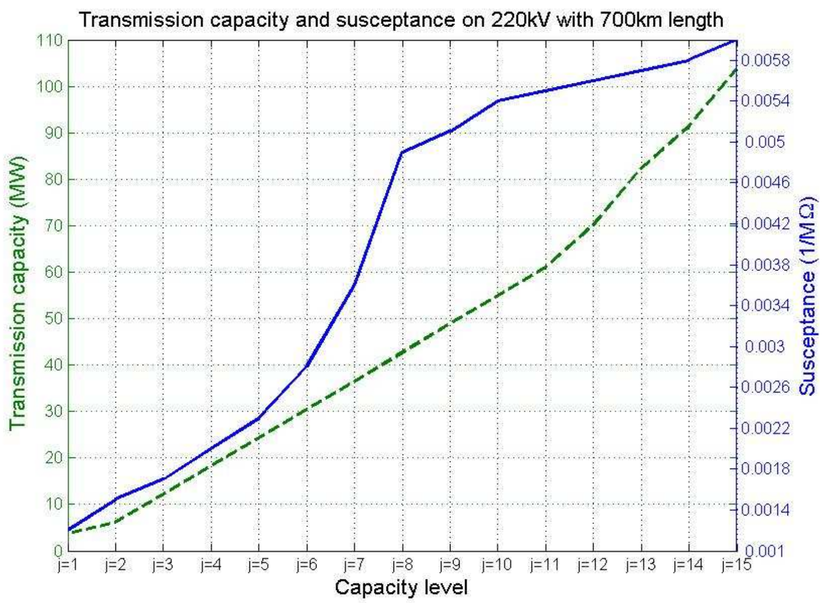


Figure 4.4: Transmission Line Parameters

4.4.2 Computational Issues

The problems are implemented in GAMS running on a Windows workstation with a 3.30 GHz Intel i7 core processor and 16 GB RAM. While the MI's MPEC is re-formulated as an MILP, the CP's MINLP and the TSO's MPEC are re-formulated as MIQPs. All problems are solved via GUROBI. Computational times with two periods and two scenarios range from less than one second (CP and all TSO instances) to 855 s (MI with PC) and 7735 s (MI with CO). In the latter instance, there are 3,481 equations, 1,520 continuous variables, and 484 discrete variables. The relative optimality gap is set to 5%.

4.4.3 Example 1: Base Case without RPS

As a benchmark, we find that the CP simply matches the most efficient resource with the most valuable demand nodes (Table 4.2). The conventional producer at node 1 serves all of the local demand, while transmission lines are constructed from nodes 2 to 3 with an effectively zero expected profit, $\mathbb{E}[\overline{\Pi_{n,i}}]$, for producers if the subsidy on congestion rent from the CP and the legacy capacity for the conventional producer are ignored. Moreover, the expected profit from grid operations, $\mathbb{E}[\overline{\Pi^{arc}}]$, is negative as congestion rents are internalised in a centrally planned economy. Meanwhile, the TSO's result under perfect competition is similar to that of the CP aside from the levying of congestion rents, which drives the producers' expected profits to zero (with the exception of the conventional producer). This is in contrast to Sauma and Oren (2006) because of the difference in formulation: we have sales and dispatch decisions made by producers, whereas Sauma and Oren (2006) assume that only dispatch is made by producers with sales and flow decisions performed by a welfare-maximising TSO. The MI under perfect competition delivers a lower social welfare because of its incentive to maximise its own expected profit, which is attained by reducing line capacities to boost congestion rents. Consequently, the producers adopt less generation capacity, and the expected nodal prices and differences in expected congestion rents are higher. For example, under the MI, it costs a perfectly competitive producer at node 2 nearly €16/MW to send power to node 3 as opposed to about €4/MW with a TSO. Hence, the MI delivers lower social welfare and less renewable generation than the TSO.

Under a Cournot oligopoly, producers have the incentive to withhold generation capacity in order to boost expected profits. Anticipating this strategic behaviour, the TSO supports expected SW by effectively subsidising wind generation by investing heavily in line 1. This creates an opening for the wind producer at node 2 to benefit at the expense of the conventional producer at node 1. Consequently, the generation investment and operations observed under perfect competition are altered as a result of the exercise of market power by the producers and the countervailing decisions of the TSO at the upper level. For an MI, the strategic withholding by producers at the lower level is likewise undesirable because it cuts into transmission flows. Recognising this, the MI mitigates losses to its profit by encouraging transmission. Thus, for different reasons than the TSO, the MI also invests in more distinct lines under Cournot oligopoly than under perfect competition. However, total transmission capacity drops under the Cournot setting because of the producers' propensity to withhold generation and the MI's reluctance to subsidise wind to increase social welfare. Finally, although the MI's actions result in wind investment at node 3, expected renewable generation, $\mathbb{E}[\overline{\mathrm{RG}}]$, is greatest under the TSO.

4.4.4 Example 2: Renewable Portfolio Standards

Given that the EU's 2030 objective is to decrease CO_2 emissions by 40% relative to 1990 levels, i.e., implying a deep decarbonisation of the power sector, we run our model with an RPS target of 80% (Table 4.3). We find that the effective subsidy for wind (and tax on conventional generation) enables the high penetration of renewables seen under Cournot oligopoly in Table 4.2 to be achieved here even under perfect competition. In effect, RPS mimics the high renewable penetration with alteration of generation patterns under oligopoly.

4.4.5 Larger Problem Instances

In order to investigate the robustness of our insights, we also implement two additional examples. For the three-node network with four scenarios and eight time periods, computational times for the CP and TSO market designs are again less than one second. However, those for the MI market designs balloon to 9 h (with PC) and 35 h (with

Table 4.2: Results for Example 1

	Cournot Oligopoly		Perfect Competition		CP
	MI	TSO	MI	TSO	
$\mathbb{E}[\overline{SW}]$	3549.50	3860.19	4073.66	4154.39	4154.69
$\mathbb{E}[\overline{\text{RG}}](\%)$	46.80	87.83	39.65	44.83	44.83
$\mathbb{E}[\overline{\Pi^{arc}}]$	63.72	-4351.73	155.27	20.97	-29.17
$\sum_{j\in\mathcal{J}_1} u_{1,j}K_{1,j}^{arc}$	3.70	61.00	0.00	0.00	0.00
$\sum_{j\in\mathcal{J}_2} u_{2,j}K_{2,j}^{arc}$	6.10	30.50	12.20	24.40	24.40
$\sum_{j\in\mathcal{J}_3} u_{3,j}K_{3,j}^{arc}$	0.00	0.00	0.00	0.00	0.00
$\mathbb{E}[\overline{flow_1}]$	-3.67	-58.45	0.00	0.00	0.00
$\mathbb{E}[\overline{flow_2}]$	6.10	29.52	12.20	24.05	24.05
$\mathbb{E}[\overline{flow_3}]$	0.00	0.00	0.00	0.00	0.00
$\mathbb{E}[\overline{p_1}]$	58.41	36.81	33.58	33.58	33.58
$\mathbb{E}[\overline{p_2}]$	43.31	51.06	31.82	31.84	31.84
$\mathbb{E}[\overline{p_3}]$	48.17	30.48	47.80	35.95	35.95
$\mathbb{E}[\overline{\tau_1}]$	-6.76	22.31	0.47	-0.16	-
$\mathbb{E}[\overline{\tau_2}]$	-12.29	76.07	-1.30	-1.90	-
$\mathbb{E}[\overline{\tau_3}]$	0.00	44.90	14.69	2.21	-
$\mathbb{E}[\overline{\Pi_{1,1}}]$	1100.45	233.60	188.70	188.70	182.68
$\mathbb{E}[\overline{\Pi_{2,2}}]$	592.09	4672.03	0.00	0.00	56.15
$\mathbb{E}[\overline{\Pi_{3,3}}]$	33.05	0.00	0.00	0.00	0.00
$g_{1,1}^{inv}$	32.91	0.00	61.42	61.42	61.42
$g_{2,2}^{inv}$	121.56	356.34	167.94	207.35	207.35
$g_{3,3}^{inv}$	12.74	0.00	0.00	0.00	0.00

CO). Nevertheless, the qualitative insights are similar to those in Example 1. For a six-node network (Fig. 4.5) with eight candidate transmission lines, computational times for the CP and TSO market designs are about four minutes, and the results are as for the three-node network, i.e., transmission lines are built to transfer the wind power to consumption centres. However, the MI market designs become more challenging to solve without recourse to decomposition, which is an area for future work.

4.5 Discussion and Conclusions

Deregulation of the power sector has created various market designs to balance competing economic and social objectives. Here, we take a complementarity approach to compare MI and TSO market designs in analysing a transition to a more sustainable electricity industry. By re-formulating the bi-level problems as MPECs and then as MILPs or MIQPs, we implement these market designs for a three-node example and along with an RPS requirement. We demonstrate how market design and market power interact to result in seemingly counterintuitive outcomes. In particular, we note that under the CP and TSO (with perfect competition) market designs, the results are similar. Intuitively, the conventional producer satisfies all of the local demand, while a transmission line linking nodes with wind producers is constructed. This results in generation expansion by the conven-

Table 4.3: Results for Example 2

	Cournot Oligopoly		Perfect Competition		CP
	MI	TSO	MI	TSO	
$\mathbb{E}[\overline{SW}]$	2705.35	3860.18	3084.858	4073.84	4073.84
$\mathbb{E}[\overline{\text{RG}}](\%)$	80.10	87.80	80.10	81.57	81.57
$\mathbb{E}[\overline{v}]$	48.85	0.00	49.07	4.09	-
$\mathbb{E}[\overline{\Pi^{arc}}]$	576.93	-4351.73	1010.291	158.68	-39.61
$\sum_{j\in\mathcal{J}_1} u_{1,j}K^{arc}_{1,j}$	12.20	61.0	18.30	48.80	48.80
$\sum_{j\in\mathcal{J}_2} u_{2,j}K^{arc}_{2,j}$	12.20	30.5	6.10	24.40	24.40
$\sum_{j\in\mathcal{J}_3} u_{3,j}K^{arc}_{3,j}$	3.70	0.00	0.00	0.00	0.00
$\mathbb{E}[\overline{flow_1}]$	-12.20	-58.44	-18.30	-48.25	-48.25
$\mathbb{E}[\overline{flow_2}]$	8.08	29.524	6.10	23.68	23.68
$\mathbb{E}[\overline{flow_3}]$	-3.70	0.00	0.00	0.00	0.00
$\mathbb{E}[\overline{p_1}]$	79.80	36.80	72.83	36.85	36.85
$\mathbb{E}[\overline{p_2}]$	40.94	51.06	22.44	31.26	31.26
$\mathbb{E}[\overline{p_3}]$	47.48	30.47	49.89	36.33	36.33
$\mathbb{E}[\overline{\tau_1}]$	-10.48	11.94	-9.698	2.80	-
$\mathbb{E}[\overline{\tau_2}]$	3.50	11.65	0.076	0.00	-
$\mathbb{E}[\overline{\tau_3}]$	-0.32	13.44	0.00	2.50	-
$\mathbb{E}[\overline{\Pi_{1,1}}]$	286.29	233.60	188.70	188.70	243.42
$\mathbb{E}[\overline{\Pi_{2,2}}]$	844.81	4672.02	0.00	0.00	143.57
$\mathbb{E}[\overline{\Pi_{3,3}}]$	33.73	0.00	0.00	0.00	0.00
$g^{inv}_{1,1}$	0.51	0.00	5.38	9.90	9.90
$g^{inv}_{2,2}$	164.49	356.34	239.84	368.89	368.89
$g^{inv}_{3,3}$	18.09	0.00	8.897	0.00	0.00

tional producer and the cheaper (on-shore) wind producer, and power flows towards the location of the more expensive (off-shore) wind producer. The MI market design under perfect competition is qualitatively similar in terms of transmission investment, generation expansion, and power flows. However, since the MI is concerned about maximising its own expected profit only, it strategically invests in less transmission capacity to increase congestion rents, thereby earning positive expected profit. The expected generation from renewables is similar to that under the CP and TSO (with perfect competition) market designs.

Allowing for market power at the lower level leads to less generation investment as producers seek to drive up the market-clearing price. Under the TSO market design with a Cournot oligopoly, the conventional producer's act of withholding investment, indeed, increases its own expected profit and average prices across the network. However, this withholding could have a deleterious effect on social welfare, which the TSO seeks to mitigate by effectively subsidising more transmission investment along lines involving the on-shore wind producer. Consequently, this countervailing action by the TSO creates an opening for the on-shore wind producer to expand generation capacity in order to offset some of the effects of the market power exercised by the conventional producer. Somewhat counterintuitively, expected generation from renewables increases significantly with a Cournot oligopoly vis-à-vis perfect competition, and the on-shore wind producer

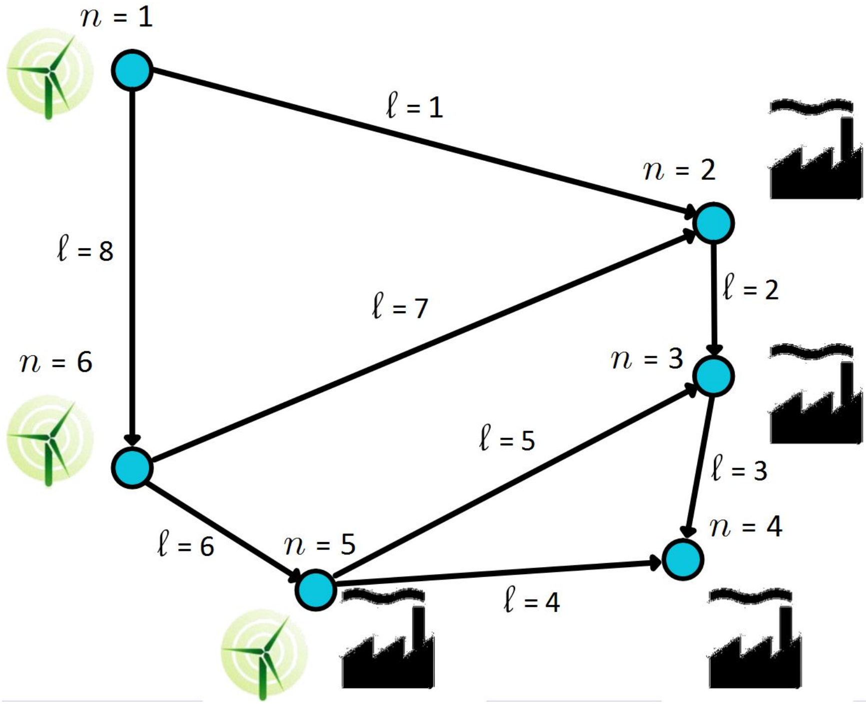


Figure 4.5: Transmission Network with 6 Nodes

actually exports power to the conventional producer's node.

This rather surprising result is also encountered in the MI market design with a Cournot oligopoly but for different reasons. As with the TSO, the lower level now has producers with the incentives to withhold generation capacity in order to increase expected profits and prices. However, such behaviour will conflict with the MI's objective to maximise expected profit, which consists of the product of congestion rents and power flows. Since the latter are adversely affected by the producers' withholding, the MI takes countermeasures to prevent power flows from dropping too much. Thus, it also invests in lines connecting the on-shore wind producer with the rest of the network, albeit by much less than the TSO. This enables power generation by not only the on-shore wind producer but also the more expensive off-shore wind producer. With an RPS constraint, the enhanced role for wind producers supported by complementary transmission investment is observed even when the lower level does not have producers behaving à la Cournot. Hence, the desirable policy target of significant renewable penetration may be attained (even in the presence of conflicting game-theoretic incentives) without the need to tolerate market power.

Chapter 5

Summary and Conclusions

In the next 25 years, energy demand is projected to grow by 1.5% annually, amounting to a 50% expansion compared to today's demand levels (EIA, 2013). While estimates might differ, there is unanimous agreement that the energy use will increase dramatically over the coming years. Hence, in order to meet future energy demands, wide-ranging investments and technological developments will be required.

Since the 1990s, to encourage more efficient electricity generation, a number of countries have undertaken steps to increase competition in their electricity industry. The main driving force behind the deregulation has been to lower electricity prices and to spur technological innovation. The more competition, the more likely the electricity prices are to reach the limits set by the fuel costs. However, due to exercise of market power by power companies in lightly regulated industries, deregulation has not achieved this goal yet. At the same time, deregulation has led to higher price uncertainties. Another factor playing an important role in the energy industry is the need to reduce CO_2 emissions to mitigate the effects of climate change. Emissions from power stations using fossil fuels account for approximately 30% of the total greenhouse gas emissions in the EU (WRI, 2008). Thus, improving the energy efficiency of fossil-fired power plants is one of the keys to reducing greenhouse gas emissions. Parry et al. (1999) argue that the most efficient solution would be to price the negative externalities of coal- and gas-fired generation effectively, i.e., to introduce taxes on emissions. However, such policies have garnered limited political support (Borenstein, 2011). Hence, many governments have preferred to create policies to promote renewable electricity generation more directly, i.e., by introducing subsidies. This has led to a large increase in intermittent generation in the EU, which means that unpredictable weather conditions play an ever-increasing role in electricity generation, and, hence, in determining electricity prices. Therefore, to counter the effects of uncertain energy prices triggered by deregulation and increased intermittent generation, large consumers need to apply risk management to energy procurement.

These two factors have also affected generation and transmission investments. TSOs need to invest in new lines in order to integrate new wind generation, but in a deregulated industry they do not have the means to recoup their capital costs directly or to control generation investment decisions.

The objective of this thesis has been to address these two problems, viz., the risk management of a microgrid with physical and financial hedges and transmission expansion with concurrent wind energy investments. Chapter 2 focused on the investment decision of a large consumer and showed that, for consumers facing electricity and heat demand, CHP can be efficiently used not only to decrease the running costs but also to hedge against price jumps. In order to provide deeper insights into risk management and operational flexibility, Chapter 3 proceeded with the medium-term management problem of a microgrid with installed CHP. It was found that CHP as a physical hedge is more efficient in reducing the microgrid's risk exposure than the available financial products. Finally, in Chapter 4, the joint problem of wind energy investment and transmission expansion was considered, along with an examination of the role that market designs and the producers' market power can play in accommodating transmission expansion and investments in wind energy. We find that it is in the interest of both the TSO and the MI, albeit for different reasons, to mitigate the restrictive behaviour of the incumbent producer in a Cournot oligopoly, which can support policies towards profit-oriented transmission expansion.

5.1 Optimal Selection of Distributed Energy Resources under Uncertainty and Risk Aversion

According to the US Environmental Protection Agency (EPA, 2012), an additional 40 GW of CHP generation capacity, i.e., an increase of around 50% from the current level, would save 293 TWh of energy, reduce CO_2 emissions by 150 million tons, and result in savings of around $10 billion for consumers per year. In line with these findings, a number of countries are aiming to accelerate investment in CHP. In Germany, over the last twelve years, the government has removed barriers and introduced subsidies to promote CHP development. Despite these efforts, however, customers' adoption of cogeneration is lagging behind the targets. The European Association for the Promotion of Cogeneration (European Cogeneration Review - Germany, 2013) argues that the main reasons behind the low adoption rate are the volatile gas spark spreads and risk aversion among the smaller potential investors.

To provide investment decision support, we develop a mean-risk optimisation model for the long-term risk management problem of a hypothetical microgrid using mixed-integer, multi-stage stochastic programming. We find that investing in CHP reduces the expected energy costs of a microgrid significantly compared to purchasing electricity from the market or generating without heat recovery. More important, with an adequate risk management strategy, on-site generation can lead to a lower risk exposure compared to purchasing electricity from the spot market. Due to its high efficiency, CHP facilitates risk management even when the expected gas spark spread is negative. As CHP can swap electricity with high volatility for gas with low volatility, investing in CHP is somewhat similar to purchasing a swaption, an option to exchange the streams of payments with different volatilities. Thus, CHP can be regarded as a physical hedge, and, consequently, it also interacts with financial hedges. In particular, we find that electricity futures and on-site generation are substitutes, while gas futures and on-site generation are complements. Nevertheless, the degree of both substitution and complementary effects depends on the level of risk aversion. We note that, with higher electricity price volatility, the value of on-site generation as a physical hedge increases as compared to financial hedges. On the other hand, under lower levels of electricity and gas price correlations, on-site generation works less efficiently as a physical hedge, but the complementary effect of the gas futures increases. Accordingly, improving the liquidity of the gas futures market can contribute to better customer adoption of the DG.

As an analysis focusing on the long-term decisions, this work is limited by some simplifications that enabled the investment problem to be computationally feasible. Since the quarterly average spot prices have a lower volatility than the hourly spot prices, using them underestimates the CVaR-reducing impact of the CHP. Furthermore, while yearly futures are available, consumers can also purchase weekly and monthly electricity futures for the base load, peak load, and off-peak load periods as well as monthly gas futures, a fact that increases the CVaR-reducing potential of financial hedging. Besides improving the granularity of the decision making, as a next step, we would also like to investigate path-dependent investment decisions, which could shed light on the use of real options in risk management (Wang and Neufville, 2004). Another direction for future work is to examine the same problem using the linear decision rule approach which, unlike scenario tree-based approximations, provides scalable optimisation models (Rocha and Kuhn, 2012).

5.2 Optimal Operation of Combined Heat and Power under Uncertainty and Risk Aversion

In addition to examining the long-term investment decisions, large consumers also need to take into account operational decisions when considering the risk management of a microgrid. For this reason, the focus of this study is on the optimal operation of a microgrid with installed CHP in the medium term. We present a multi-stage stochastic mean-risk optimisation model, which can be used to reduce the risk exposure of a microgrid through on-site generation and electricity and gas futures purchases. We examine a one-month operational period, and, to make the study problem as realistic as possible, we incorporate all the available financial products from the EEX Phelix Futures market. The microgrid can purchase monthly electricity futures with an off-peak load, a peak load, or a base load profile, as well as weekly electricity futures contracts for the base load and peak load periods. Furthermore, the microgrid, with an installed CHP unit, can generate electricity using gas from the spot and monthly futures markets, while recovering the waste heat. To supply additional heat, the microgrid can produce heat with the boiler unit also, using gas from the spot and monthly futures markets.

Similarly, as in the long-term management problem, we find that a microgrid with CHP can lower its running costs significantly and reduce its risk exposure as well. Comparing on-site generation with heat recovery and that without it, we find that an installed MT unit can lower the operational costs of the microgrid but to a much smaller extent than a CHP unit. Furthermore, while operating an MT unit reduces the CVaR in absolute terms due to the lower running costs, it increases the CVaR of the microgrid relative to its expected cost. In contrast to on-site generation without heat recovery, using a CHP unit reduces the CVaR by a wider margin both in absolute and relative terms and results in a preferential distribution of the relative standard deviation of operational costs. Thus, while results of the dissertation's investment model assert that a MT with and without heat recovery can function as a physical hedge, we find that from a medium-term perspective only a CHP can take this role. By implementing different types of futures contracts, we also gain a better understanding into interactions of physical and financial hedges. In particular, with increased risk aversion, the substitution effect of on-site generation with CHP for monthly base load futures decreases. Such interactions can be exploited only through sophisticated decision support systems that can enable consumers to decide on their optimal hedging levels. Advanced microgrids are capable of integrating multiple DERs, e.g, wind and solar power, and energy storage as well, and may even sell electricity to the grid. Exploring operational risk management in such microgrids is worthy of a future study (Lasseter, 2011; Lidula and Rajapakse, 2011).

5.3 Transmission and Wind Investment in a Deregulated Electricity Industry

In the EU, annual investments in wind power have increased from around 3.2 GW in 2000 to 11.2 GW in 2013, with a total installed capacity of 117.3 GW (Wind Energy report, 2014). Since wind power is inherently variable and uncertain due to weather factors, the continuously increasing wind power capacity negatively affects transmission networks. In fact, the European Network of Transmission System Operators for Electricity (ENTSO-E) has identified 100 bottlenecks in its network development plan (European Transmission

System Operators, 2012) with 80% of them related to the integration of renewables. Not only do such bottlenecks result in high electricity prices but also they can lead to blackouts. In fact, most of the major blackouts in the US over the last 35 years have been linked more to transmission problems than to generation (Lévêque, 2006).

Thus, maintaining a reliable power supply necessitates investments in both national and cross-border electricity transmission. In the EU, the total investment requirement for the high-voltage grid is estimated to be between €68-104 billion (European Climate Foundation, 2012; von Hirschhausen et al., 2014; Egerer et al. 2013). In addition to imposing such huge financial burdens, the transmission expansion projects are also known to be intriguingly complex. First, transmission planning needs to consider both short-term dispatch efficiency and long-term incentives for generation investment. Second, in the context of a deregulated electricity industry, the incumbent and future generators, or retail companies, all have conflicting interests and might try to influence the relevant decision makers (Lévêque, 2006). While some generators will argue for more transmission to gain access to new markets, others will argue against transmission expansion to keep local prices high and maintain their market power. From the perspective of the retail companies, more transmission results in lower costs and weakened market power for the incumbent producers.

In order to gain insight into the transmission expansion problem, generation investments need to be considered concurrently. We develop a stochastic bi-level programming model that, depending on the market design, has either an MI or a TSO making transmission investment decisions at the upper level, and power producers - both wind and conventional - determining generation investment and operations at the lower level. First, these problems are formulated as MPECs, and then, by re-formulating them as MILPs or MIQPs, we solve them for a three-node example. To provide policy insights into the increasing renewable generation, we include also the RPS requirement. The interaction of market design and market power, i.e., either perfect competition or Cournot oligopoly, is examined. We find that, in a perfectly competitive market, wind producers are limited by the incumbent conventional producers, regardless of whether it is the TSO or the MI that makes the transmission expansion. In contrast, somewhat counterintuitively, oligopolistic behaviour by the producers creates an opening for the wind producers because of withholding by the incumbent producer. To mitigate the decreased SW under Cournot oligopoly, the TSO needs to build more lines than under perfect competition and has to subsidise electricity transmission effectively. Correspondingly, the MI builds a lower transmission capacity but more lines to increase the transmission flows in an attempt to maximise its expected profits. Thus, for distinctly different reasons, greater renewable penetration is observed than under perfect competition. However, with an RPS policy, greater renewable penetration can be achieved even under perfect competition.

Although this study reflects the salient features of the power sector, such as the strategic behaviour, loop flows, and variable, non-dispatchable wind output under different market designs, it may be enhanced further. Possible pathways for extension are implementation of the models on more realistic test networks, a larger number of scenarios for the wind output and a bi-level representation of the producers' behaviour, which will necessitate recourse to decomposition algorithms. Furthermore, in this study we assume that the lower-level decisions of the producers are open loop, in order to have only one strategic decision maker at the upper level. Relaxing this supposition to have a closed-loop problem for some producers would lead to an equilibrium problem with equilibrium constraints (EPEC). Finally, including risk-constrained investment strategies in our model might provide better understanding of transmission expansion decisions. These additional model implementations can serve as topics for further research, which could build on the findings presented here.

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