Strategic Network Planning in Biomass-Based Supply Chains

Dissertation

to obtain the doctoral degree

of Economic Sciences (Dr. oec.)

Faculty of Business, Economics and Social Sciences

University of Hohenheim

Institute of Interorganizational Management & Performance

Department of Supply Chain Management

submitted by:

M.Sc. Stephan Fichtner

from Backnang

Stuttgart 2021

Supervisor:	Prof. Dr. Herbert Meyr
Co-Supervisor:	Prof. Dr. Katja Schimmelpfeng
Dean:	Prof. Dr. Karsten Hadwich
Date of submission:	16.06.2020
Date of disputation:	13.10.2020

Acknowledgments

The present PhD thesis was written during my time as a research assistant at the department of Supply Chain Management at the University of Hohenheim in Stuttgart. I am very grateful to all of the people, who have supported, motivated and accompanied me through this time.

First and foremost, I would like to express my deep thanks to Prof. Dr. Herbert Meyr for being my PhD supervisor. Thank you for your support and guidance during the last years. Throughout the entire project and despite your busy schedule, you always made time to discuss arising problems or to talk about the progress and the next steps of my work. You provided the opportunity to learn a lot by sharing your broad knowledge base, your experience and your analytical capability. Moreover, you always maintained a very pleasant and open communication atmosphere.

Furthermore, I would like to thank Prof. Dr. Katja Schimmelpfeng for acting not only as a second reviewer of my PhD thesis but also as kind of a second supervisor in difficult times. You always found time to discuss technical and personal issues and supported me on conferences and conventions. Thank you very much for this. Also thanks to Prof. Dr. Michael Ahlheim for being the chairman of my PhD committee.

I would like to express my gratitude as well to my current and former colleagues at the University of Hohenheim. In particular, Mirko Kiel, Jens Kärcher, Dr. Martin Wörbelauer, Dr. Jaime Cano-Belman, Dr. Ivan Zulj, Hendrik Butemann and Katrin Wauer. Thank you for your support, the fruitful discussions about teaching and research topics, for the pleasant non-scientific conversations and the great atmosphere.

Many thanks also to the members of the research group around PhD P.Eng Animesh Dutta at the University of Guelph in Canada. You made my time there helpful and wonderful.

There are many friends outside university from whom I also received support, sometimes by motivating me to finish the project, but mostly by distracting me from my daily work and having very good times. I am honestly grateful to all of you. Most of all, I am sincerely grateful to my family and Simone, who have always believed in me and have always supported me in achieving my goals. You motivated me and gave me confidence. Thank you very much for being there.

Stephan Fichtner

Contents

List of Figures

List of Tables

1 Introduction

The present thesis examines models for strategic network planning in biomass-based supply chains. These models are used to increase the profitability of products, produced in biomass-based supply chains to make them more competitive. Within the subsequent section, the main motivation of this thesis is described. Additionally, the considered strategic planning level in this industry and the reason for planning in general are explained. Section 1.2 formulates the research objectives of the thesis and explains, which methods are used to reach these objectives. Finally, Section 1.3 describes the detailed outline of the thesis.

1.1 Motivation

Technological progress and the associated development of prosperity in industrialized countries is often accompanied by the exploitation of natural resources or increasing environmental pollution. To overcome negative accompanying symptoms of the industrial progress, a transformation of the traditional economic system towards a "bioeconomy" has become an important approach. The concept of bioeconomy is a composite of biology and economy. (Kaltschmitt, 2009) It describes the knowledge-based production and usage of renewable resources (biomass) for products, processes and services in all industrial sectors and thus a pre-requisite to form a sustainable economy. In this case, problems like the feeding of a growing global population, sustainable energy production or reduced usage of scarce resources like crude oil can be solved by using biomass as a resource. (Pyka, 2017; Lewandowski et al., 2018) As already mentioned, the basis of such a bioeconomy are renewable feedstocks in form of biomass. All living materials with organic origin are types of biomass. That means that plants and animals as well as their residues are part of biomass. Furthermore, dead phytomass, as for example straw, is biomass, too, if it is not yet fossil. Moreover, everything which can be put into a biowaste container could be used as biomass feedstock. The process of rotting constitutes the differentiating characteristic between biomass and fossil resources. For example, peat is already rotten and thus not regarded as biomass anymore. (Kaltschmitt, 2009)

The utilization pathway with the final product energy generated in biogas plants using biomass can be mentioned as one example within bioeconomy. The energy production in biogas plants using a conventional plant design is depicted in Figure 1.1. In this conventional case, biomass as a substrate is used to produce biogas through a combustion process in a digester. Afterward, the produced biogas is directly burned in a combined heat and power (CHP) plant to produce electricity and the by-product heat. The biogas production within the digester is continuous. If the biogas production rate is greater than the available biogas capacity in the storage plus the amount burned in the CHP, the excess gas can be burned using a torch.

This conventional biogas plant design can be adjusted to increase the flexibility within the production processes. Several characteristics, which can be adjusted, are the type and capacity of biogas usage, the gas storage capacity on-site, the type of conversion process, and the substrate feeding management. The similarity of all those adjustments is that investments are needed to realize them. (Fichtner and Meyr, 2019)

Crucial for the success of a transition from a traditional economy towards a bioeconomy is the economic profitability. In times of low commodity prices, e.g. for crude oil, producing energy and other products like plastics from biomass is significantly more expensive than exploiting fossil resources. Hence, to establish a successful

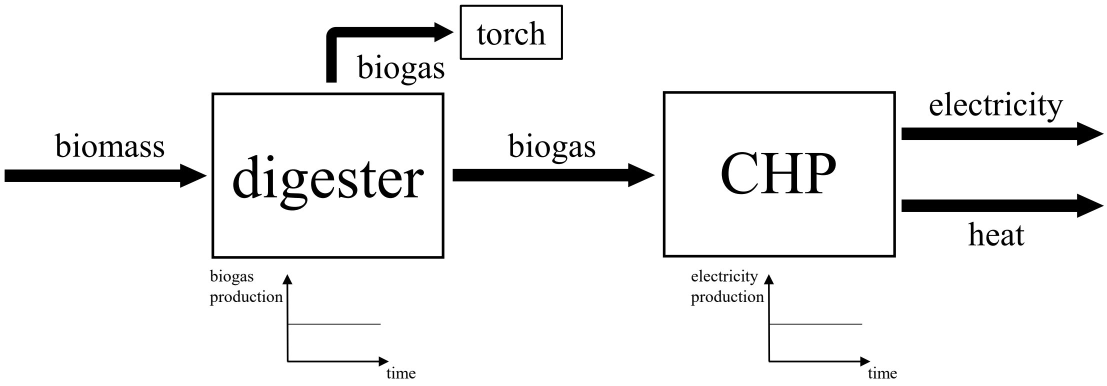

Figure 1.1: Conventional biogas plant configuration (see Fichtner and Meyr (2019))

bioeconomy, the costs for biomass-based products have to be decreased. One approach to reduce the costs from an organizational point of view is the application of advanced supply chain planning.

Planning in general is very important for every organization. For instance, if a manufacturer needs production materials from suppliers that are far away, the materials have to be ordered early enough considering the transportation time and potential interruptions during the logistical processes. Particularly, planning is used to prepare upcoming decision problems as good as possible. This means that several alternatives have to be identified, evaluated and then an ideally optimal one should be chosen. (Fleischmann and Koberstein, 2015)

Typically, an organization is not considered as an individual entity. Instead, it is regarded as part of a supply chain, where a supply chain is, according to Christopher (2005, p. 17), defined as a "...network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate consumer". This definition can be extended into intra-organizational in a narrow and inter-organizational supply chains in a broader sense according to Stadtler (2015).

The so-called supply chain planning represents the decision support concerning all planning problems along the entire supply chain. Within Figure 1.2 a general overview of typical planning tasks, arising in a supply chain, is provided. As depicted, the planning tasks of a supply chain are structured by the main supply chain processes procurement, production, distribution and sales and classified by the length of the planning horizon into long-, mid- and short-term planning. Typically, a long-term planning horizon covers several years. Between half a year and two years is considered in mid-term planning and the short-term planning is characterized by a horizon of a few days up to three months. During long-term planning tasks, decisions with an impact on the long-term structure of the supply chain are made. These decisions are called strategic decisions. The mid-term planning is often named as tactical planning. Within this tactical planning, a rough plan of material flows is defined within the boundaries of strategic planning. In contrast, short-term operational planning is used for detailed production, transportation and scheduling tasks. (Fleischmann et al., 2015)

As shown in Figure 1.2, the introduced planning levels are linked hierarchically and horizontally by occurring information flows. In order to support the supply chain planning through all planning levels and tasks, software, named Advanced Planning Systems, can be used. Using these software packages an optimal or at least a very good plan for combined planning tasks can be found. The theoretical basis of these systems are often methods of operations research. (Fleischmann et al., 2015)

Operations research describes a field of research that deals with the analysis of practical, complex problems within the framework of a planning process to prepare the best possible decisions by applying mathematical methods. The main tasks in operations research are the representation of a real decision problem by an optimization or simulation model and the application or development of an algorithm to solve the problem, often supported by software applications. (Domschke et al., 2015)

As previously explained, typical for biomass-based supply chains is the cost issue compared to the traditional fossil-based industry. Since this is a fundamental issue, according to several entire supply chains, it has to be tackled on a strategic planning level to take the whole supply chain into account. Decisions on the strategic level typically involve substantial investments and show long-lasting effects over several years or even decades because they cannot easily be revised again. Because of their high importance, these decisions should be made carefully. To support them, the mentioned operations research models can be used.

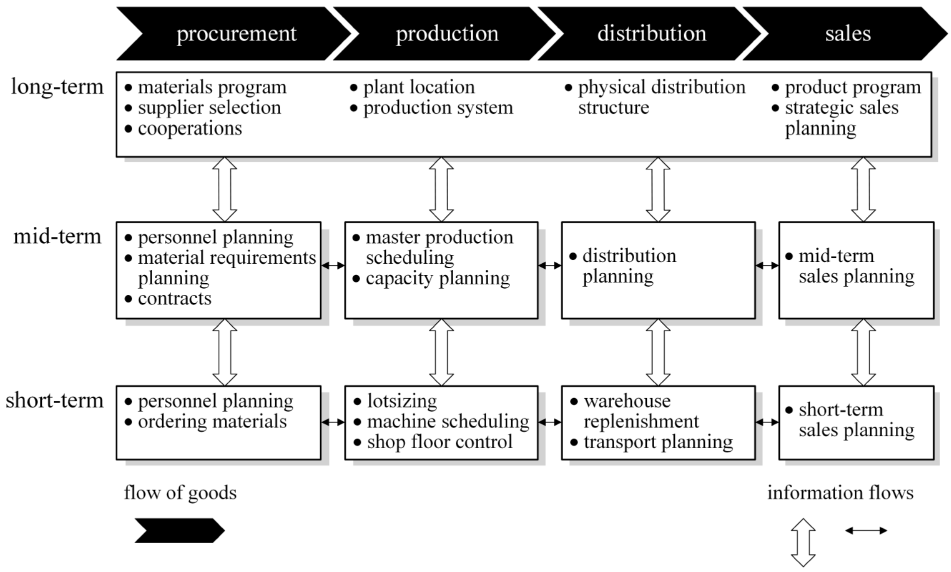

Figure 1.2: Supply chain planning matrix (see Rohde et al. (2000); Fleischmann et al. (2015))

1.2 Research objectives and methodology

As already addressed in Section 1.1 the research field of bioeconomy is in its infancy. Nevertheless, it is a very diverse field of research. Dealing with the great diversity within the field leads to the first research objective.

> ***Research objective 1:***
>
> *Structured analysis of the landscape of strategic long-term supply chain planning problems within bioeconomy.*
>
> ***Sub-objective 1.1:***
>
> *Clustering of sub-problems in branches and identification of specific characteristics.*
>
> ***Sub-objective 1.2:***
>
> *Identification of research gaps regarding strategic planning in biomass-based supply chains.*

In order to reach research objective 1, a structured review of recent literature on the long-term, strategic planning of biomass-based supply chains is conducted. During this process, the entire research field of bioeconomy and not only a single, specific branch like the fuel area is embraced. However, the focus is on publications applying quantitative simulation and optimization models, as commonly done in operations research. All in all several dozen publications are considered. For these publications, important characteristics are identified and classified using a classification scheme, which allows easy comparison of the different modeling approaches. This helps to reveal current trends and gaps as well as opportunities for future research. One of the identified research gaps is to make biomass-based supply chains profitable on their own, i.e., without governmental subsidies. Therefore, new optimization models are necessary, which should be as close to reality as possible, by for example considering risks, arising through prices, demand and supply uncertainties, and actual surrounding constraints concerning the legal framework. This leads to research objective 2.

> ***Research objective 2:***
>
> *Strategic optimization of biogas plants considering increased flexibility.*
>
> ***Sub-objective 2.1:***
>
> *Structured analysis of technical and legal circumstances.*
>
> ***Sub-objective 2.2:***
>
> *Analysis and forecasting of energy spot market prices.*
>
> ***Sub-objective 2.3:***
>
> *Development of a robust optimization approach.*

In a second part of the thesis one specific strategic supply chain planning problem, in one biomass-based supply chain is tackled. Particularly, biogas plants as part of the energy supply chain are investigated. In the first step, to reach the first sub-objective of research objective 2, the legal circumstances are determined using literature research. These legal circumstances in Germany are mainly included in the renewable energy resources act (EEG). Additionally, the technical framework of biogas plants is analyzed. In a second step, the characteristics of energy spot market prices are evaluated. Therefore, methods of descriptive statistics are used to emphasize characteristic elements like existing seasonalities and trends. Based on the results of the descriptive statistics a forecasting function is generated, which is used to generate future scenarios. In a third step, a novel multi-stage deterministic optimization approach is developed. Therefore, at first, a basic model to optimize the operational plant schedule called OBPP (operational biogas plant problem) is introduced. Secondly, this model is extended to support investment decisions regarding the flexibility potential of the biogas plant (SBPP - strategic biogas plant problem). In general, to increase the flexibility of existing biogas plants, investments in an adjusted plant configuration are necessary. To evaluate several investment alternatives, the strategic optimization model is used. Besides, as the spot market prices are varying dynamically over time because of the uncertain behavior of energy demand and supply, this variation is analyzed and considered using several scenarios. Therefore, significant sources of uncertainty are analyzed and determined. In order to reach a robust solution for the strategic investment planning problem, methods of decision theory are applied. Since such a robust optimization approach considering and modeling the technical characteristics of biogas plants and legal requirements of the EEG, challenged in sub-objective 2.3, does not yet exist, its development represents the innovative part and thus the main contribution of the entire thesis.

> ***Research objective 3:***
>
> *Economic optimization of biogas plants considering variable substrate feeding.*
>
> ***Sub-objective 3.1:***
>
> *Linear approximation of non-linear biogas production rates.*
>
> ***Sub-objective 3.2:***
>
> *Extension of the developed optimization approach regarding variable substrate feeding.*

As shown in the literature (see, e.g., Barchmann et al. (2016), Grim et al. (2015), Mauky et al. (2016)) the consideration of variable substrate feeding and thus a demand-oriented biogas production can influence the optimal operational biogas plant schedule and thus the optimal flexible plant design. Particularly, the necessary biogas storage capacity can be reduced. In order to consider the economic influence of variable substrate feeding on the decisions in the previously developed optimization approach, the variable biogas production rates have to be included in the optimization models. To evaluate the behavior of biogas production rates, based on variable substrate feeding, the related literature is analyzed in a first step. On this basis, it is determined that resulting biogas production rates follow a non-linear pattern. Thus, in a second step, two approaches are introduced to approximate the non-linear patterns using piecewise linearization and using Rieman sums. Based on these approximations, the process of variable substrate feeding is included in the operational and strategic optimization models. The modeling of this extension represents the major objective of the third part of the thesis. Additionally, the economic effects of variable substrate feeding on the operational biogas plant schedule are investigated using numerical experiments. These experiments are focused on the general effects of variable feeding compared to fixed feeding, the mixture of several variably fed substrates and the substrate prices. As it is not possible to solve the extended strategic optimization model optimally using standard solvers, approaches for simplifications or heuristic solutions are sketched.

1.3 Outline of the thesis

The detailed agenda of the present thesis is organized as follows. Chapter 2 provides a structured literature review, which has already been published as a chapter in the collected volume by Dabbert et al. (2017). (Fichtner and Meyr, 2017) After an introduction, the overall research field bioeconomy by means of the various utilization pathways of biomass is structured in Section 2.2. Supply chain management is – despite its name – rather demand- than supply-oriented. The customer and her/his requested final items are in the center of the thoughts. However, Section 2.2 takes a different view. Here, the scarce resource biomass, i.e., the ultimate supply, is the starting point. If the best possible utilization of this scarce resource has to be identified, all different utilization pathways originating from and competing for the same biomass need to be analyzed. This may comprise hundreds and thousands of different final items and customers. Thus, Section 2.2 lays the ground for bringing together the demand-oriented view of supply chain management models and the supply-oriented view of bioeconomy. Section 2.3 provides the literature review of operations research models and methods for strategic supply chain planning in biomass-based industries. Section 2.4 draws conclusions by analyzing trends and research gaps. Finally, Section 2.5 summarizes the results and identifies opportunities for future research.

Chapter 3 comprises a paper titled "Biogas plant optimization by increasing its flexibility considering uncertain revenues", which represents the main part of the entire thesis. This paper has been written by Stephan Fichtner and Herbert Meyr. The paper has been published as one of the Hohenheim Discussion Papers in Business, Economics and Social Sciences. (Fichtner and Meyr, 2019) A short introduction describes current opportunities and challenges in the German energy market. Additionally, the beneficial role of biomass as a feedstock of biogas plants for electricity and heat production is characterized. In Section 3.2 an overview of the problem setting is given. Therefore, the market conditions in terms of spot market prices, direct marketing and the electricity demand are introduced. Furthermore, the functionality of biogas plants is explained. Subsequently in Section 3.3 relevant literature is analyzed. The literature review is focused on operations research-based literature, dealing with uncertainty in biogas plants or related energy sources. Subsequently, a research gap is identified. Within Section 3.4 a deterministic optimization approach to fill this research gap is described. Here, a multi-stage optimization approach consisting out of operational and strategic optimization models, an approach to generate scenarios for stochastic input data and a decision theory-based approach to generate a robust solution is introduced. The developed approach is subsequently tested using a fictional but close to reality case example in Section 3.5. Finally, Section 3.6 summarizes the results and identifies opportunities for extensions or general future research.

Chapter 4 comprises a working paper titled “Operational and strategic optimization of biogas plants based on variable substrate feeding”, which proposes an extension of the developed optimization models of the previous chapter regarding variable substrate feeding. This paper has been written by Stephan Fichtner. Section 4.1 provides an introduction explaining the extended parts and new objectives regarding the modeling of the economic influence of variable substrate feeding. In Section 4.2, a technical overview of biogas production using variable substrate feeding is given. The overview is focused on the technical influences of variable substrate feeding on the operation of a biogas plant and its appropriate plant design before challenges and opportunities of variable substrate feeding are discussed. Subsequently in Section 4.3 relevant literature is analyzed. Here, the approach of Fichtner and Meyr (2019) is combined with related literature concerning technical aspects of variable substrate feeding. Within Section 4.4 the optimization approach of Fichtner and Meyr (2019) is extended in terms of applying variable substrate feeding. Therefore, the non-linear biogas production rates are approximated using two approaches in Section 4.4.1 in a first step. Subsequently, the two optimization models OBPP and SBPP are extended in Section 4.4.2. The extended models are then tested using numerical experiments in Section 4.5. Several effects are sequentially analyzed in this subsection. First, the general economic effect of variable substrate feeding compared to fixed feeding is investigated. Second, the effects of different variably fed substrates are investigated. Third, the effect of feedstock prices is measured. Afterward, a strategic optimization considering variable substrate feeding is sketched. Finally, Section 4.6 summarizes the results and identifies opportunities for further extensions or general future research.

Chapter 5 is divided into two subsections. The first one summarizes the content of the thesis and the second one provides an outlook on further research topics.

Bibliography

Barchmann, T., Mauky, E., Dotzauer, M., Stur, M., Weinrich, S., Jacobi, F., 2016. Erweiterung der Flexibilität von Biogasanlagen – Substratmanagement, Fahrplansynthese und ökonomische Bewertung. Landtechnik Agricultural Engineering 71, 233–251.

Christopher, M., 2005. Logistics and supply chain management, creating value-adding networks. 3 ed., Financial Times Prentice Hall, Harlow.

Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), 2017. Knowledge-driven developments in the bioeconomy. Economic complexity and evolution, Springer Verlag, Cham.

Domschke, W., Drexl, A., Klein, R., Scholl, A., 2015. Einführung in Operations Research. 9 ed., Springer Berlin Heidelberg, Berlin, Heidelberg. doi:10.1007/978-3-662-48216-2.

Fichtner, S., Meyr, H., 2017. Strategic Supply Chain Planning in Biomass-Based Industries: A Literature Review of Quantitative Models, in: Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), Knowledge-driven developments in the bioeconomy. Springer Verlag, Cham. Economic complexity and evolution, pp. 259–291.

Fichtner, S., Meyr, H., 2019. Biogas plant optimization by increasing its flexibility considering uncertain revenues. Hohenheim Discussion Papers in Business, Economics and Social Sciences 07, 1–48. Stuttgart.

Fleischmann, B., Koberstein, A., 2015. Strategic Network Design, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 107–123. doi:10.1007/978-3-642-55309-7_6.

Fleischmann, B., Meyr, H., Wagner, M., 2015. Advanced planning, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 71–95. doi:10.1007/978-3-642-55309-7_4.

Grim, J., Nilsson, D., Hansson, P.A., Nordberg, Å., 2015. Demand-Orientated Power Production from Biogas: Modeling and Simulations under Swedish Conditions. Energy & Fuels 29, 4066–4075. doi:10.1021/ef502778u.

Kaltschmitt, M., 2009. Biomasse als nachwachsender Energieträger, in: Kaltschmitt, M., Hartmann, H., Hofbauer, H. (Eds.), Energie aus Biomasse: Grundlagen, Techniken und Verfahren. 2 ed.. Springer Berlin Heidelberg, Berlin, Heidelberg. chapter 1.1, pp. 1–7.

Lewandowski, I., Gaudet, N., Lask, J., Maier, J., Tchouga, B., Vargas-Carpintero, R., 2018. Introduction, in: Lewandowski, I. (Ed.), Bioeconomy. Springer International Publishing, Cham, pp. 1–2. doi:10.1007/978-3-319-68152-8_1.

Mauky, E., Weinrich, S., Nägele, H.J., Jacobi, H.F., Liebetrau, J., Nelles, M., 2016. Model Predictive Control for Demand-Driven Biogas Production in Full Scale. Chemical Engineering & Technology 39, 652–664. doi:10.1002/ceat.201500412.

Pyka, A., 2017. Transformation of Economic Systems: The Bio-Economy Case, in: Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), Knowledge-driven developments in the bioeconomy. Springer Verlag, Cham. Economic complexity and evolution, pp. 3–16.

Rohde, J., Meyr, H., Wagner, M., 2000. Die Supply Chain Planning Matrix. PPS Management 5, 10–15.

Stadtler, H., 2015. Supply Chain Management – An Overview, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 3–28. doi:10.1007/978-3-642-55309-7_1.

2 Strategic Supply Chain Planning in Biomass-Based Industries — A Literature Review of Qantitative Models

Abstract[1] Fossil resources are limited and will run short. Moreover, the extensive usage of fossil resources is discussed as a key driver for climate change which means that a changeover in basic economic and ecological thinking is necessary. Especially for the energy production, there has to be a movement away from the usage of fossil resources and towards renewable resources like wind, water, sun or biomass. In this chapter we present a structured review of recent literature on the long-term, strategic planning of biomass-based supply chains. Firstly, we structure the overall research field "bioeconomy" by means of the various utilization pathways of biomass and bring together the demand-oriented view of supply chain management models and the supply-oriented view of bioeconomy. Secondly, we provide a literature review of operations research models and methods for strategic supply chain planning in biomass-based industries. Thirdly, we analyze trends and draw conclusions about research gaps.

Keywords Bioeconomy, Strategic Supply Chain Planning, Review

2.1 Introduction

In recent years global economy has continuously improved (World Bank, 2015). The leading industrial nations have achieved an enormous wealth. Furthermore, there is also an increasing wealth in threshold countries. However, this global wealth is largely based on the usage of finite fossil resources like crude oil, coal and natural gas. Fossil resources are limited and will run short. In addition, the extensive usage of fossil resources is recognized as a key driver for climate change. As a consequence, a changeover in basic economic and ecological thinking is necessary. Especially for energy production, there has to be a movement away from the usage of fossil resources towards renewable resources like wind, water, sun or biomass. For the remainder of this chapter, we define all not yet fossil materials with organic origin as types of biomass. That means that plants and animals as well as their residues are biomass, but also dead phytomass, as for example straw, can be biomass, as long as it is not yet fossil.[2]

Note that using biomass for various production processes is not a new idea. Decades ago, before the industrial revolution, the global economy was significantly more biomass-based than today. Nevertheless, in the future a more efficient use of biomass will be required not only to tackle the above challenges, but also to mitigate the increasing world food problem. The industrial use of biomass can provide a building block of a more sustainable economy, which in the following will be called "bioeconomy". A crucial barrier for leveraging bioeconomy are costs. In current times of extremely low crude oil prices, producing energy and other products like textiles from

[1] This paper has been written by Stephan Fichtner and Herbert Meyr (Department of Supply Chain Management, University of Hohenheim, Stuttgart). The paper has already been published as a chapter in the collected volume by Dabbert et al. (2017). (see Fichtner and Meyr (2017))

[2] A more detailed definition will follow in Section 2.2.

biomass is significantly more expensive than exploiting fossil resources. Hence, the costs of the bioeconomy have to be decreased. This could be achieved by technological innovation as well as by optimized organization. Since many parties are involved in converting biomass in more valuable final items like energy and (or) in transporting it to the final consumers (for usage as food), a large part of the total costs of biomass usage is caused by logistical processes. Thus, a clever management of biomass-based supply chains (SCs) is necessary.

In this chapter we present a structured review of recent literature on the long-term, strategic planning of biomass-based SCs. We try to embrace the whole research field of bioeconomy and not only a single, specific branch like the fuel area. However, we focus on publications applying quantitative simulation and optimization models, as commonly done in operations research (OR). All in all we consider several dozen publications. Thus it is not possible to discuss each model in detail. Instead, we identify the – in our opinion – most important characteristics of these models to introduce a classification scheme which allows an easy comparison of the different modeling approaches. This helps to reveal current trends and gaps as well as opportunities for future research. To the best of our knowledge, there is no prior review with a focus on all of these aspects.

The remainder of this chapter is organized as follows. In Section 2.2 we structure the overall research field "bioeconomy" by means of the various utilization pathways of biomass. Note that supply chain management (SCM) is – despite of its name – rather demand- than supply-oriented. The customer and her/his requested final items are in the center of the thoughts. All parties cooperating to fulfill the final customer's demand should try to integrate as good as possible in order to offer highest customer service for lowest costs. Thus, the members of a single SC should act as partners in a team; but different SCs have to compete with each others for this final customer's demand. Section 2.2 additionally takes a different view. Here, the scarce resource biomass, i.e., the ultimate supply, is the starting point. If one likes to judge about the best possible usage of this scarce resource, all different utilization pathways originating from and competing for the same biomass need to be identified. This may comprise hundreds and thousands of different final items and customers. Thus, Section 2.2 lays the ground for bringing together the demand-oriented view of SCM models and the supply-oriented view of bioeconomy. Section 2.3 provides the literature review of OR models and methods for strategic SC planning in biomass-based industries. Section 2.4 draws conclusions by analyzing trends and research gaps. Finally, Section 2.5 summarizes the results and identifies opportunities for future research.

2.2 Biomass-based supply chains

In Section 2.2.1 biomass is used as the starting material to identify different utilization pathways and their resulting final products. These final products are then the starting point to determine the corresponding types and members of supply chains in Section 2.2.2 and to structure the literature review of Section 2.3.

2.2.1 Utilization pathways of bioeconomy

A biomass-based utilization pathway is a specific sequence of process steps or processes (e.g., harvesting/collection, pre-processing, conversion) to generate a biomass-based final product. These pathways are investigated in the research area "bioeconomy", which is a composite out of biology and economy (Kaltschmitt, 2009). It is the knowledge-based production and utilization of renewable resources for products, processes and services in all industrial sectors and thus a pre-requisite to form a sustainable economy (BMBF and BMEL, 2014). As already mentioned, the basis of such a bioeconomy are renewable feedstocks in form of biomass. All living materials with organic origin are types of biomass. That means that plants and animals as well as their residues are part of biomass. Furthermore, dead phytomass, as for example straw, is biomass, too, if it is not yet fossil. Moreover, everything which can be put into a biowaste container could be used as biomass feedstock. The process of rotting constitutes the differentiating characteristic between biomass and fossil resources. For example, peat is already rotten and thus not regarded as biomass anymore (Kaltschmitt, 2009).

Figure 2.1 offers a simplified overview of utilization pathways that are investigated in bioeconomy. Traditional illustrations, e.g. by Kaltschmitt (2009, Fig. 1.2) for energetic usage of biomass, are more detailed and show a stronger focus on the conversion technologies that are currently technologically feasible. However, for our purposes a more simplistic view will be sufficient. Thus, four different types of biomass are identified: plants, wood, residuals and living beings. These four groups contain all the materials which have in the above definition been characterized as biomass. Those different types of biomass have to be converted after their cultivation, harvesting and collection. Mainly three different conversion technology groups need to be distinguished, which are the thermo-chemical, the bio-chemical and the phyiscal-chemical conversion. Intermediate products are created through those technologies and finally transformed into a large variety of final products. The German "Bioökonomierat" groups the final products into the five different types food, feed, fibre, fuel and "flowers and fun" (Bioökonomierat, 2015). Because feed is usually indirectly used to produce food, we pool both in a more comprehensive group "food production".

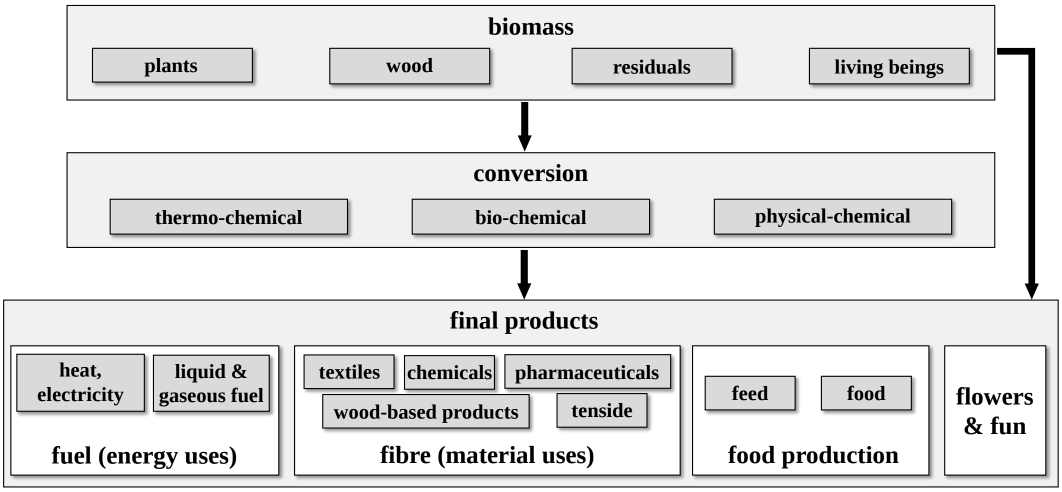

Figure 2.1: Simplified utilization pathways of bioeconomy

Many different ways are possible through this network. With respect to the identified groups of final products, Sections 2.2.1.1–2.2.1.4 give some further information on these possibilities. Furthermore, Section 2.2.1.5 uses the example of municipal waste to illustrate how the different utilization pathways of a specific type of biomass can look like.

2.2.1.1 Fuel

A large variety of utilization pathways ends up in the final product "fuel". All four groups of biomass can be the starting material. For example, many different types of plants can be used to produce fuel in general. Possible plants are lignocellulosic plants like miscanthus, reed or millet, oleiferous plants like rape, sunflower or soy, starchy plants like potatoes, maize or grain and sugar-containing plants like sugar beet and cane. Additionally, wood out of short-rotation coppice, the traditional forest wood and residuals could be used. The residuals can further be classified into waste timber, agricultural residuals like straw or liquid manure and municipal waste. It is also possible to generate fuel from micro- or macro-algae which would be categorized as “living beings”. These types of algae cannot yet be produced and exploited on an industrial scale. However, they could be an opportunity for the future (Kaltschmitt, 2009).

Biomass utilization pathways are always feedstock-oriented. As a consequence, for every type of biomass like for example rape or municipal waste, a specific utilization pathway has to be distinguished. Exemplary utilization pathways for municipal waste will be shown in Section 2.2.1.5 below. Nevertheless, the steps of such a path can roughly be divided into the biomass collection, a specific chemical conversion technology and the production of the final product out of intermediate products of the conversion. Thermo-chemical conversion technologies used for fuel production are, for instance, combustion, gasification and pyrolysis, whereas fermentation and aerobic decomposition are examples for bio-chemical conversion technologies. Additionally, also physical-chemical conversion technologies can be used to produce fuel, e.g., by extracting biodiesel from rape. All in all, a large variety of biomass can be processed using these three different types of conversion technologies, which again can be subdivided into various specific treatments (Kaltschmitt, 2009).

Thus, many different utilization pathways for the final product “fuel” do exist. However, as Figure 2.1 shows, “fuel” is again just used as a generic term for a whole class of final products transforming biomass into energy. Such final products are, for instance, liquid & gaseous fuels like bioethanol, biodiesel and hydrogen. Apart from that there are also heat and electricity generation subsumed under this type. Heat and electricity are often generated simultaneously by using so called “combined heat and power plants” (e.g., burning of biogas). However, it is also possible to produce heat apart from electricity, e.g., by combustion.

2.2.1.2 Fibre

A similarly large variety of biomass types as for fuels can be used to produce final products of the fibre type. Fibre denotes tangible products that are neither used for energetic purposes nor for food production. As Figure 2.1 shows, these “material uses” of biomass are manifold and can further be classified into textiles (and textile fibres, respectively), wood-based products (like wood fibres, paper, cartoon, but also furniture, floorboards or timbers), chemicals, pharmaceuticals and tensides.

The already described conversion technologies can also be applied to gain fibres. However, because of the many and very different final products subsumed here, with pulping, cutting and chemical synthesis some additional conversion technologies of the physical-chemical type can be used. Thus, a greater number and a greater heterogeneity of utilization pathways can be found. To give an example: it is obvious that the production process of timber (mainly sawing, drying and moulding, maybe jointing) is very different to the production of bioplastics, which is rather a sort of chemical product. Thus the different pathways can span from traditional and comparably simple conversion technologies like cutting and extraction to more advanced ones like fermentation. All in all, this great diversity of pathways and final products is characteristic for the group “fibre” (Türk, 2014).

2.2.1.3 Food production

The area “food production” concerns both the intermediate product “feed” for the breeding of farm animals as well as the various types of food for human beings. Thus, all types of groceries (ranging from fruit, vegetables and cereals, via fish, meat or other products of animal origin like eggs and cheese, to combinations thereof as, for example, convenience foods), but also feed for animals and even fertilizers are included. (Bioökonomierat, 2015)

In contrast to the utilization pathways so far presented, the ones ending up in feed or food do not use all types of biomass. For example, woody biomass does not matter in food production.

The relevant biomass is not only processed by means of the earlier described conversion technologies, but also directly used. This “unconverted utilization” is the main distinguishing feature between the pathways described so far and the ones considered here. Although the variety of potential feed and food conversion technologies is still high, it appears lower than for fuel and fibre because both source materials and final products are less heterogeneous. For instance, thermo-chemical conversion techniques are mainly used for cooking or baking convenience food. Here, source materials and final products are homogeneous enough to allow a cost-efficient conversion on an industrial scale. Although there are some exceptions, in general the structure of the biomass feedstock is less modified than in the prior pathways.

2.2.1.4 Flowers & fun

The final products' group "flowers" comprises uneatable horticultural products like ornamental plants and turf rolls. The importance of this industry heavily depends on regional aspects. For instance, the flower industry in Belgium or the Netherlands is much more important than the one in Germany. "Fun" focuses on the usage of biomass for extraordinary leisure activities. Examples are turf-rolls for football stadiums or golf courses that are built on former farm land. Obviously, even less and more specific types of biomass are relevant for this area. Utilization pathways are also fewer and simpler because conversion is of minor importance or no importance at all. Instead, efficiency and speed of transportation might become more crucial. All in all, as compared to the other groups of final products discussed before, this area only plays an insignificant role. It will thus not further be discussed in the remainder of this chapter.

2.2.1.5 Example: municipal biowaste as starting material

To illustrate how different utilization pathways can origin from the source material "biomass", municipal waste is taken as an example. Municipal biowaste consists of biodegradable garden waste and compostable food waste like fruit and vegetable peelings, i.e., it belongs to the "residuals" class of biomass presented in Figure 2.1.

Exemplary utilization pathways of municipal waste are shown in Figure 2.2. Municipal waste can either be processed using the thermo-chemical conversion technology "combustion" (solid arrow) or using the bio-chemical conversion technologies "fermentation" (dashed arrow) or "aerobic decomposition" (dotted arrow).The classical way of converting municipal waste into cascading products is combustion. In this case, it is possible to produce heat apart from electricity. Note that physical-chemical conversion is not applied to municipal waste (Thrän et al., 2009).

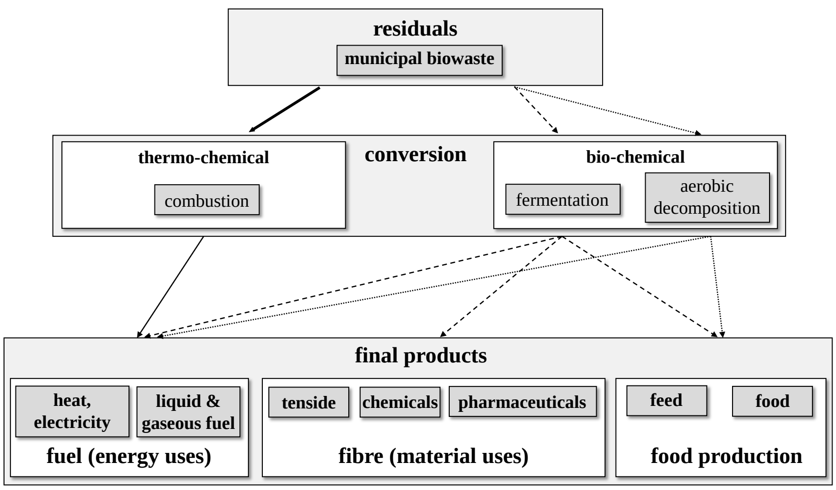

Figure 2.2: Utilization pathways of municipal waste

Besides electricity and heat also liquid and gaseous fuels could be produced from municipal waste. Material uses do at most occur for tensides, chemicals and pharmaceuticals, but not for textiles and wood-based products. Since fertilizer results as a by-product of bio-chemical conversion (e.g., in biogas refineries), municipal waste might indirectly contribute to feed and food production when cultivating the farm land (Diepenbrock, 2014). However, such utilization pathways do not play an important role.

2.2.2 Supply chains

In Section 2.2.1, the various utilization pathways have been considered that start from the source material "biomass". However, the aim of this chapter is to review the literature about the strategic planning of biomass-based *supply chains*. Thus, it is first necessary to define the terms "supply chain", "supply chain planning" and "strategic planning". Secondly, differences and similarities between supply chains and the utilization pathways considered so far have to be discussed.

2.2.2.1 Supply Chain Planning

Christopher (2005, p. 17) defines a *supply chain* as a "...network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate consumer." Stadtler (2015, p. 3f.) further differentiates between SCs in a broad and in a narrow sense. In a broad sense, such an SC consists of two ore more legally separated organizations, which are linked by flows of material, information and funds (so-called "inter-organizational" SCs). In a narrow sense, an SC can also be a single, large company which consists of several departments and/or sites that might be spread over different countries and even continents ("intra-organizational"). Managing the same flows might here be easier since all of the different parties belong to the same company. Nevertheless, because of the size of such companies, this is usually still very complex. Thus, decision making needs to be supported.

SC planning offers this decision support for the various planning tasks arising in supply chains by building simplified models of the real SCs, deriving solutions for these models, and interpreting these solutions in order to solve the original, real-world problem. Such models might be forecasting models, which try to predict the future, optimization models, which try to find the best solution out of a huge number of alternative, feasible solutions, or simulation models, which cost-efficiently try to mimic the behavior of complex multi-stage SCs in sufficiently detailed computer models (Fleischmann and Meyr, 2003; Fleischmann et al., 2015).

Strategic SC planning aims at offering this decision support for all planning problems that concern the design and long-term structure of supply chains. Such decisions typically involve substantial investments (e.g., for establishing a cooperation, building a new factory or introducing new products in unexploited markets) and show long-lasting effects over several years or even decades because they cannot easily be revised again. Because of their high importance, these decisions are usually made by the top management(s) of the company (or the companies) involved. Nevertheless, they can be pre-selected and evaluated in terms of their advantages and disadvantages by computer systems and the staff departments of the companies. These decisions should be comprehensive and thus consider all relevant material and financial flows (e.g., fixed costs for investments, variable sales revenues and operational costs) of the SC as a whole — from raw material supply, through the various conversion processes in the different production sites up to the sales to the ultimate consumers. This includes the necessary transportation and storage processes to bridge space- and time-related discrepancies.

2.2.2.2 Differences between supply chains and utilization pathways

When looking at these definitions some differences between supply chains and the utilization pathways discussed so far become obvious.

As already mentioned, utilization pathways are feedstock-oriented, starting with (in the future probably scarce) biomass as the source material. In contrast supply chains are customer- and product-focused. The final customer and her/his desired product should be in the center of all thoughts.

Furthermore, utilization pathways are mainly focusing on the material flow, i.e., the materials involved and the technologies to convert these materials. Often life-cycle-analyses (LCAs) are executed to evaluate and compare the ecological impacts of different pathways. If economic effects are considered at all, they are usually estimated for whole (sectors of) economies. In contrast, supply chains are only interested in the economic benefits of their own members. This does usually either comprise a single company (intra-organizational SC) or only a few collaborating companies (inter-organizational SC). However, this economic benefit is of very high importance because it justifies the existence and ensures the survival of the SC. Thus it is necessary to stress monetary aspects that are not at all considered in utilization pathways. Such aspects are, for example, the allocation of profits to the various participants of the SC or the sharing of costs for joint appliances or services.

Besides these monetary effects, other benefits (e.g., increased visibility) and risks (e.g., loss of autonomy, cheating) may depend on cooperation and coordination aspects of SC planning.

Figure 2.3 gives an example of the different parties that may be involved in biomass-based SCs. By using Figure 2.1 as a basis, we link the customer-oriented view of SCs with the biomass-based view of utilization pathways. As can be seen, many different parties have to work together if a supply chain wants to become and stay successful. For sake of clarity, we did not even include service providers of support processes like transportation, storage, cutting / compacting and drying. Remember that SCs producing similar – or, to be more precise, in the customers' perception substitutable – final products compete with each other. Thus innovative biomass-based products are in competition with traditional fossil-based products. For example, energy from biogas refineries competes with energy from power stations burning natural gas. Although governmental subsidies can support the development and market entry of ecologically preferable, biomass-based products, they are usually only granted for a limited time span. Afterward, the corresponding biomass-based supply chains have to be profitable on their own and, furthermore, stand the competition with other biomass-based and the traditional fossil-based SCs. Thus, a mere concentration on utilization pathways would be too short-sighted. SC planning aspects, as briefly addressed here and reviewed in Section 2.3, should be taken into consideration from the very first beginning.

Figures 2.1 and 2.3 can give some clues on the competition between SCs offering substitutable products. For example, in the case of electricity, biomass-based electricity has to compete with other renewable energies like solar power or wind, with nuclear power and with fossil-based energies stemming from coal, mineral oil and natural gas. The grid operators and energy companies transport and sell the electricity to the customers. Thus, they have to ensure that a customer can buy the specific mix of energy (s)he wants to get. As another example, liquid automotive fuels are mainly sold by mineral oil companies via their network of petrol stations. There is a competition within a single petrol station between products containing different shares of biomass-based ethanol, but also between the fuels of different mineral oil companies. When considering the SCs providing these final products we can see that innovative biomass-based SCs for fuel and fibre mainly compete with traditional SCs of the energy, mineral oil, chemical, pharmaceutical and textile industries. SCs offering wood-based fibres and food, however, have always relied on biomass as their primary source material. A lot of scientific research has already been done for these latter types of SCs. Our review in Section 2.3 will thus rather concentrate on the former "innovative" types biomass-based SCs and just refer to already existing review papers for the latter types.

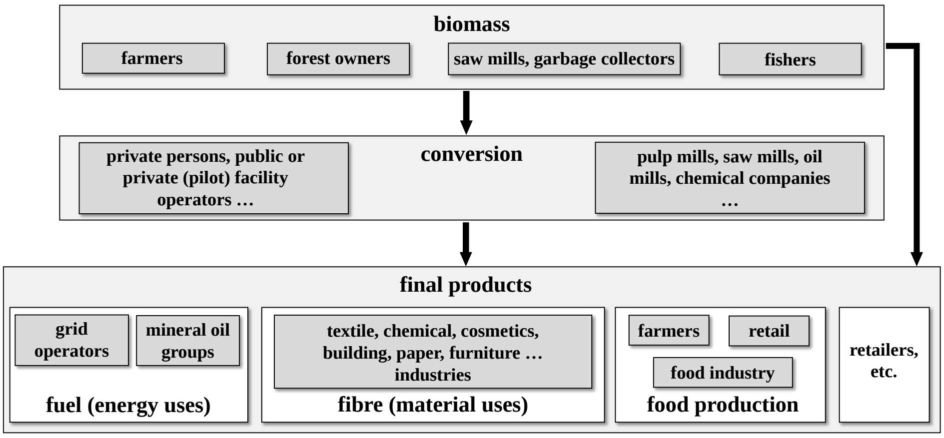

Figure 2.3: Potential members of biomass-based supply chains

2.2.2.3 Similarities

Despite of these differences, utilization pathways and SCs both illustrate the flow of materials from the supply of the raw materials, through a network of transforming facilities to the final products. Thus utilization pathways help to identify and model biomass-based SCs.

Note that the material flows presented in Figures 2.1–2.3 had been simplified to allow and emphasize the clustering of the various biomass sources, conversion technologies, final products and potential SC members into catchy classes. For the review of Section 2.3, the structure presented in Figure 2.4 will be more appropriate.

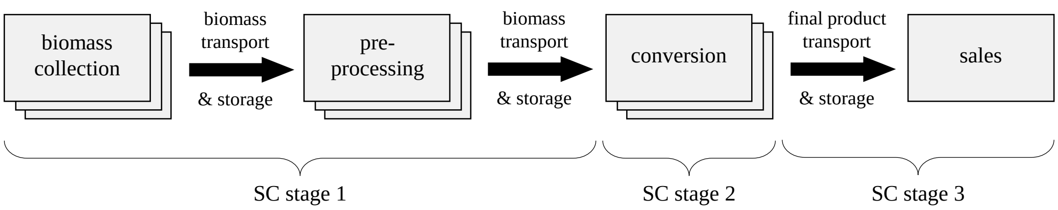

Figure 2.4: Supply chain stages

Up to three stages of a SC will be distinguished. Stage 1 includes the different biomass collection processes, like harvesting or the collection of residuals, and the transport to and storage at certain collection points. Seasonal storage of biomass feedstock is necessary because of the seasonal availability of biomass and the great uncertainty concerning quantity and quality. Additionally, but not necessarily, pre-processing activities and their respective transport and storage processes are also included in stage 1. Pre-processing is often necessary because the original biomass shows a high content of water and a low energy density. By processes like cutting, compacting and drying, both energy density and transportation efficiency are increased.

Stage 2 comprises the whole (in itself maybe again multi-stage) production network of the SC, i.e., all conversion, transportation and storage processes that are necessary to transform (pre-processed) biomass into the final product. This may regard only a single, but also several alternative conversion technologies if a single SC simultaneously comprises several utilization pathways. The specific conversion technologies are depending on the type of the final products. Chemical products are mainly produced in biorefineries, which are similar to classical petroleum refineries.

Stage 3 finally includes the transport and storage of the final products and the corresponding sales activities. Note that supply and demand usually do not occur at the same point in time. Supply is, for example, bound to the harvesting times of biomass, which may be seasonal. Demand is determined by the customers' wishes and expectations. Thus storage processes are necessary to bridge the time lag. In general, these storage processes may occur at any stage of the SC. However, it has to be taken into account that biomass and its resulting intermediate products often are perishable and either can only be stored for a limited amount of time or have to be made more durable somehow, e.g., by drying. Nevertheless, as a rule of thumb, it is preferable that storage processes occur early in the material flow, i.e., upstream in the SC. At early stages of the SC the value of the respective intermediate products is still low so that storage costs are not yet crucial.

2.3 Literature review

In the following we survey the recent research on quantitative models for the long-term, strategic planning of biomass-based SCs. 70 journal publications, regarding biomass-based fuel and fibre SCs, have been analyzed. They have been published since the year 1997. However, their majority stems from the year 2011. Altogether 33 different journals are concerned. Thereby the journal "Biomass and Bioenergy" shows the greatest share with 12 references. 48 references regard biofuel SCs, 21 electricity and 12 heat SCs. Further 12 references relate to fibre SCs. Thus some journal publications refer to several types of biomass-based SCs.

The references have been analyzed using a common scheme that is expressed by the columns of Table 2.2. First of all, we are interested in the type of quantitative model that has been used (column "O./S."). Here optimization ("O") and simulation ("S") models are distinguished. The optimization models are further classified into deterministic ("det") and stochastic ("sto") models. Deterministic means that all input parameters of the model are assumed to be deterministically known, whereas stochastic models assume that at least one uncertain random variable exists. Furthermore, we are interested in the optimization models' objective functions (column "obj"). The models pursue monetary ("mon"), ecological ("eco") or social ("soc") objectives, either separately or simultaneously as part of a multi-objective optimization (indicated by a "/"). The column "SC stages" shows which of the three stages introduced in Figure 2.4 is/are actually considered by the model. The column "biomass type" finally denotes the type of biomass concerned. All four types of biomass introduced in Section 2.2.1 and Figure 2.1 are possible, i.e., plants, wood, residuals ("resi.") and living beings ("beings").

Sections 2.3.1 and 2.3.2 discuss strategic models of the fuel and the fibre areas in sufficient detail. Readers who would additionally be interested in quantitative models on the tactical and operational planning of biomass-based SCs are referred to the reviews of An et al. (2011b), Awudu and Zhang (2012) and Ba et al. (2015). As mentioned before, the area "food production" will not be discussed in detail. Recent reviews concerning quantitative models to plan feed and food SCs can be found in Table 2.1.

2.3.1 Fuel

Due to the substantial research effort in biofuel SCs, in the following we further distinguish between biofuel (Section 2.3.1.1) and electricity and heat (2.3.1.2) supply chains.

2.3.1.1 Biofuel

Ahn et al. (2015) consider a three-stage SC producing biodiesel from microalgae, i.e., living beings are the biomass feedstock. A multiperiod, deterministic optimization model takes decisions about transportation quantities and biorefinery locations. The objective is to minimize the total costs. Akgul et al. (2012b) assess multi-objective

Table 2.1: Literature food/feed

author	title
Ahumada and Villalobos (2009)	Application of planning models in the agri-food supply chain: A review
Amorim et al. (2013)	Managing perishability in production-distribution planning: A discussion and review
Akkerman et al. (2010)	Quality, safety and sustainability in food distribution: A review of quantitative operations management approaches and challenges
Dabbene et al. (2014)	Traceability issues in food supply chain management: A review
Soysal et al. (2012)	A review on quantitative models for sustainable food logistics management
Tsolakis et al. (2014)	Agrifood supply chain management: A comprehensive hierarchical decision-making framework and a critical taxonomy
Zhang and Wilhelm (2011)	OR/MS decision support models for the specialty crops industry: A literature review

performance aspects in hybrid first and second generation bioethanol SCs. They decide about local biomass and import quantities, conversion quantities, biorefinery locations and capacities. A deterministic, multi-objective optimization model is used. The two objectives are to minimize the total costs as well as the carbon emissions of the SC. Again, the model covers the "whole" three-stage SC. With plants, wood and residuals, three different types of biomass can serve as input. Akgul et al. (2012a) take a hybrid first and second generation biofuel SC of UK's biofuel industry into account. In contrast to the model before, only a single objective is pursued. This deterministic model also covers the whole SC with plants, wood and residuals as biomass feedstock. In another work of Akgul et al. (2011), several models to optimally design a three-stage bioethanol SC are presented. The deterministic, single-objective models try to optimize the locations and capacities of bioethanol production facilities as well as the biomass and bioethanol transport flows by minimizing the total SC costs. Only plants are the possible biomass feedstock. Within these three models a development is noticeable from single- to multiple-feedstock and from single- to multi-objective modelling.

Aksoy et al. (2011) present a model configuring an SC with four different conversion technologies. All these technologies use woody biomass and mill wastes as feedstocks. The objective of the deterministic optimization model is to minimize the total costs. The model considers only the second stage of the SC, where decisions about the conversion technology are made. An et al. (2011a) also present a model to design a lignocellulosic biofuel SC. The deterministic optimization model is multi-period and multi-commodity. This means that, in contrast to other analyzed models, several kinds of biofuels are considered. The objective is to maximize the discounted profit of the SC. The whole SC from the biomass feedstock supplier up to the biofuel customer is taken into consideration. Again, plants, wood and residuals are the possible feedstocks.

Andersen et al. (2012) design and plan a three-stage biodiesel SC. The characteristic feature of their model is to consider land competition. The multi-period, deterministic optimization model maximizes the net present value. Only plants are possible feedstocks. Bai et al. (2011) propose a deterministic optimization model for biorefinery location planning by minimizing the total system costs. Special about their three-stage SC is that traffic congestion can be taken into account. Only plants are considered as possible feedstocks. Bernardi et al. (2013) propose a multi-objective model to design and plan a three-stage bioethanol SC, which includes first and second generation biorefineries. The deterministic, multi-period optimization model maximizes the net present value, minimizes carbon emissions and minimizes water consumption. Possible feedstocks are plants and residuals.

Bowling et al. (2011) place a biorefinery into an SC consisting of only the first two stages. Specific final products are not distinguished, but, for example, biofuel could be produced. Their deterministic model maximizes total profits with respect to nonlinear economies of scale. Information about possible feedstocks is missing. Cambero et al. (2015) deterministically optimize the mix of bioenergy and biofuel production within a three-stage SC using forest residuals as input. The objective is to maximize the net present value of investments in the conversion technologies. One of the few stochastic optimization models stems from Chen and Fan (2012). Bioethanol is produced out of waste while supply and demand of the three-stage SC are assumed to be uncertain. The two-stage stochastic model minimizes the expected total system costs of investments, production and transport.

Cobuloglu et al. (2014) focus on the farmers' point of view of switchgrass production. They consider both economic and environmental aspects. The deterministic, multi-objective optimization model maximizes the revenues of harvested switchgrass and positive ecological impacts. Their model covers just the first stage of a SC with plants as the only biomass feedstock. Correll et al. (2014) present a combined simulation and optimization approach to design the first stage of a SC for bioenergy and biobased products. Therefore, the model can be considered as a subproblem of a biofuel production network. The model compares diversified feedstocks with monocultures. The optimization part of the model is deterministic with the objective of minimizing capital investment and purchasing costs. The necessary input data are generated by simulation. Only plants are possible feedstocks. Corsano et al. (2011) design a three-stage sugar-to-ethanol SC where plants are the biomass input. The deterministic model is able to consider recycling processes while maximizing net profits, which are defined as the difference of the total revenues and the costs for sugar cane supply, production and transportation and for investments in conversion facilities and warehouses, respectively.

Dal-Mas et al. (2011) regard the design and planning of capacity investments for an ethanol SC. Uncertainties concerning both biomass production costs and the final products' selling prices are considered. Hence, the optimization model is stochastic. The objectives are to maximize the expected net present value and to minimize the financial risks. The model covers the whole SC. Only plants are possible feedstocks. The early work of De Mol et al. (1997) compares a simulation and an optimization approach concerning biomass collection for biofuel production. The former one assumes the network structure for the biomass collection as given. Whereas the latter one optimizes this structure by deterministically minimizing the total collection costs. Both models do only consider the first stage of the SC. Wood is the biomass feedstock.

Dunnett et al. (2008) simultaneously optimize production and logistics of three-stage, lignocellulosic bioethanol SCs by deterministically minimizing the respective costs. They decide whether the processing structure is rather decentral or central, i.e., whether the biomass is either pre-processed in decentral hubs and afterward converted in a centralized plant or whether it is completely processed in central facilities. Plants, wood and residuals are used as biomass feedstocks. Ekşioğlu et al. (2010) investigate the impact of intermodal facilities on the design of three-stage corn-to-bioethanol SCs. Their deterministic optimization model minimizes the total delivery costs of bioethanol. In earlier work, Ekşioğlu et al. (2009) had already analyzed and designed biomass-to-biorefinery SCs. The links between the biomass harvesting sites and the conversion plants were modeled as part of a deterministic network design problem. The objective was to minimize the total SC costs. However, only the first two stages of the SC were covered by this model. With plants, wood and residuals several biomass types were possible feedstocks.

Frombo et al. (2009a) plan the logistics of energy production from woody biomass. They compare several conversion technologies to produce different final products. Their deterministic optimization model minimizes the total costs. Wood and woody residuals are inputs to a three-stage SC. Giarola et al. (2013) design bioethanol SCs under risk management aspects. First and second generation production technologies are considered in a multi-period, stochastic optimization model with multiple objectives, maximizing the net present value and minimizing greenhouse gas emissions. The model covers only the first two stages of the SC. Plants and residuals can be biomass feedstocks. This work builds on earlier deterministic models published by Giarola et al. (2012) and Giarola et al. (2011), who considered a three-stage SC, however. Apart from that, the models share the same characteristics.

Huang et al. (2010) optimize three-stage, waste-based bioethanol SCs. Their deterministic model assesses economic potentials and infrastructure requirements by minimizing the total SC costs. Only residuals are considered as possible feedstocks. Ivanov and Stoyanov (2016) design integrated biodiesel and fossil-based fuel SCs. The deterministic optimization model considers all three stages of the SC using only plants as possible feedstocks. In addition to minimizing the total SC costs, the total life cycle greenhouse gas emissions are also minimized. Kanzian (2009) plans the logistics of wood to produce solid fuel. Using a deterministic optimization model, minimizing the total transportation costs, different demand scenarios for this fuel are evaluated and different network structures, with and without terminals, are compared. Only the first stage of the SC and only wood and woody residuals are taken into consideration.

Kim et al. (2011a) and Kim et al. (2011b) tackle similar problems. In both models, the whole three-stage biomass processing network to produce biofuel is designed. The first one is a deterministic optimization model. Its objective is to maximize the overall profits. It is assumed that the network can process plants, wood and residuals. The second, stochastic model considers uncertainty concerning supply quantities, market demand and price, as well as technology. All other modeling characteristics remain unchanged. Leão et al. (2011) optimize the logistic structure of two-stage biodiesel SCs by deterministically minimizing their costs. Small farmers providing plants are the only feedstock suppliers.

Leduc et al. (2010) plan the location of methanol production facilities converting lignocellulosic plants, wood and residuals. A deterministic optimization model minimizes the costs of the three-stage network. An earlier work of Leduc et al. (2008) tackled a similar problem. However, there only the gasification of wood and wood residuals was considered. Lin et al. (2014) integrate the strategic and tactical planning of large-scale bioethanol SCs. Apart from typical strategic decisions about the number, capacities and locations of facilities also operating schedules and inventory planning are considered. The authors deterministically minimize the annual costs of biomass-to-bioethanol conversion. All three stages, from the farmers (providing plants as the only biomass type) to the distribution of the bioethanol, are represented. The multi-objective, two-stage stochastic model of Marufuzzaman et al. (2014) concerns the production of biodiesel through wastewater treatment. It respects the impacts of different carbon regulation policies. Objectives are to minimize the annual costs of three-stage SCs and the resulting emissions.

Marvin et al. (2013) plan the locations of biomass conversion facilities and the selection of the appropriate conversion technology. Their deterministic optimization model maximizes the net present value of a three-stage SC using plants, wood and residuals as feedstocks. Marvin et al. (2012) tackle bioethanol production from lignocellulosic biomass. There, a bio-chemical conversion technology is applied. Five different types of agricultural residues are considered as lignocellulosic feedstocks. A single-objective, deterministic optimization model maximizes the net present value of the SC. Only the first two stages of the SC are planned. Biomass feedstock types are plants, wood and residuals. Mele et al. (2011) try to increase the sustainability of three-stage sugarcane-to-bioethanol SCs. The combined production of sugar and ethanol is considered by a multi-objective deterministic optimization model. The objectives are to maximize the net present value and to minimize the environmental damage, which is calculated using LCA. Plants are the only possible feedstocks.

Mohseni and Pishvaee (2016) and Mohseni et al. (2016) tackle similar problems. In both models, the whole three-stage SC network to produce microalgae-based biofuel is designed. Both approaches are using robust optimization with sensitivity analysis to minimize the total costs of the SC. As microalgae is used, living beings are the biomass feedstock. Osmani and Zhang (2013) consider the production of bioethanol from lignocellulosic plants, wood and residuals. Their stochastic model takes uncertain biomass prices, uncertain bioethanol demand and uncertain sales prices for bioethanol into account while maximizing the expected profit of a three-stage SC.

Santibañez-Aguilar et al. (2011) compare different, alternative utilization pathways. Their deterministic, multi-objective model maximizes their corresponding profits and minimizes their environmental impacts in order to grasp economic and environmental aspects, simultaneously. Only the upstream part of the SC (i.e., the first two stages) is modeled. Plants, wood and residuals are considered as possible feedstocks. Schwaderer (2012) integrates location, capacity and technology planning for SCs that use residuals as biomass. His deterministic optimization model minimizes the costs of the first two stages of such SCs. It can deal with final products of both the fuel and fibre type. The model of Tittmann et al. (2010) tackles the techno-economic planning of biofuel production. Their deterministic optimization model decides about locations and technologies of conversion facilities. Total profits are maximized – also for electricity, which comes up as a by-product of biofuel generation. Again only the first two SC stages are considered with plants, wood and residuals being the feedstocks.

Walther et al. (2012) design regional SCs for the production of second generation synthetic biodiesel. Their deterministic, multi-period optimization model maximizes the net present value of the three-stage network. Possible feedstocks are plants and their residuals. The – to our knowledge – first and only model, which also covers social objectives, has been published by You et al. (2012). The model tries to establish a sustainable, three-stage SC for producing biofuel from cellulosic biomass. Their multi-objective, deterministic model minimizes the annual total costs and greenhouse gas emissions, respectively, and maximizes the number of new jobs generated. Plants, wood and residuals can serve as cellulosic feedstocks. You and Wang (2011) plan three-stage biomass-to-liquid SCs with respect to economic and environmental aspects. They also apply a multi-objective deterministic model. However, theirs only minimizes the annual costs and the life cycle greenhouse gas emissions. Plants, wood and residuals are possible feedstocks. Zamboni et al. (2009) design three-stage bioethanol production SCs. As in the previous model, economic and environmental aspects are considered by deterministically minimizing both total costs as well as greenhouse gas emissions. Here, only plants are the feedstock. Finally, Zhang and Hu (2013) combine the strategic and operational planning of second generation drop-in-fuel production. Apart from the usual long-term aspects, further decisions on production patterns and inventories are made. Their deterministic optimization model minimizes the total annual costs. Only plants and residuals are possible feedstocks of a three-stage SC.

All references described above and their characteristics are summarized in Table 2.2. As can be seen, all authors formulate optimization models. Sometimes an additional simulation model is proposed. Only six out of 45 references use a stochastic approach in order to take uncertainty into account. Approximately a quarter of the references pursue an ecological objective additionally to the monetary one. Only a single paper furthermore considers a social objective. Most models cover the whole three-stage SC. Otherwise, at least the biomass supply or biomass conversion is represented. Many models allow several types of biomass. However, then often these types share a common characteristic, for example, all of them are lignocellulosic. This is convenient from a technological point of view because they show similar conversion properties. However, it might be less convenient from a logistical point of view because, for example, logistical processes to collect wood residuals in and from saw mills are very different from harvesting in agricultural fields or forests.

2.3.1.2 Electricity and heat

In the following we concentrate on biomass-based SCs producing electricity or heat as final products. Table 2.3 contains an overview of the respective literature. Since biofuel can be used as both a final product and an intermediate product for generating electricity, some references do appear in Table 2.2 and in Table 2.3 as well. Of course, those will not be discussed in detail a second time.

The production of heat is always a joint product in power generation. The ambition of so-called combined heat and power (CHP) plants is to produce electricity. Heat automatically emerges during this process. Since a few years, this waste product "heat" is more and more systematically used, e.g., to heat private houses or to dry (or cool) materials of nearby industrial parks. Because of these various possible uses, various stakeholders are increasingly interested in the final product heat. Table 2.3 illustrates this intended usage. Since none of its references uses

Table 2.2: Literature concerning biofuel production

	O./S.	det./sto.	obj.	SC stages				biomass type		
				1	2	3	plants	wood	resi.	beings
Ahn et al. (2015)	O	det	mon	x	x	x				x
Akgul et al. (2012a)	O	det	mon	x	x	x	x	x	x	
Akgul et al. (2012b)	O	det	mon/eco	x	x	x	x	x	x	
Akgul et al. (2011)	O	det	mon	x	x	x	x			
Aksoy et al. (2011)	O	det	mon		x			x	x	
An et al. (2011a)	O	det	mon	x	x	x	x	x	x	
Andersen et al. (2012)	O	det	mon	x	x	x	x			
Bai et al. (2011)	O	det	mon	x	x	x	x			
Bernardi et al. (2013)	O	det	mon/eco	x	x	x	x		x	
Bowling et al. (2011)	O	det	mon	x	x					
Cambero et al. (2015)	O	det	mon	x	x	x			x	
Chen and Fan (2012)	O	sto	mon	x	x	x			x	
Cobuloglu et al. (2014)	O	det	mon/eco	x			x			
Correll et al. (2014)	O/S	det	mon	x			x			
Corsano et al. (2011)	O	det	mon	x	x	x	x			
Dal-Mas et al. (2011)	O	sto	mon/mon	x	x	x	x			
De Mol et al. (1997)	O/S	det	mon	x				x		
Dunnett et al. (2008)	O	det	mon	x	x	x	x	x	x	
Ekşioğlu et al. (2009)	O	det	mon	x	x		x	x	x	
Ekşioğlu et al. (2010)	O	det	mon	x	x	x	x			
Frombo et al. (2009a)	O	det	mon	x	x	x		x	x	
Giarola et al. (2011)	O	det	mon/eco	x	x	x	x		x	
Giarola et al. (2012)	O	det	mon/eco	x	x	x	x		x	
Giarola et al. (2013)	O	sto	mon/eco	x	x		x		x	
Huang et al. (2010)	O	det	mon	x	x	x			x	
Ivanov and Stoyanov (2016)	O	det	mon/eco	x	x	x	x			
Kanzian (2009)	O	det	mon	x				x	x	
Kim et al. (2011a)	O	sto	mon	x	x	x	x	x	x	
Kim et al. (2011b)	O	det	mon	x	x	x	x	x	x	
Leão et al. (2011)	O	det	mon	x	x		x			
Leduc et al. (2008)	O	det	mon	x	x	x		x	x	
Leduc et al. (2010)	O	det	mon	x	x	x	x	x	x	
Lin et al. (2014)	O	det	mon	x	x	x	x			
Marufuzzaman et al. (2014)	O	sto	mon/eco	x	x	x			x	
Marvin et al. (2012)	O	det	mon	x	x		x	x	x	
Marvin et al. (2013)	O	det	mon	x	x	x	x	x	x	
Mele et al. (2011)	O	det	mon/eco	x	x	x	x			
Mohseni and Pishvaee (2016)	O	det	mon	x	x	x				x
Mohseni et al. (2016)	O	det	mon	x	x	x				x
Osmani and Zhang (2013)	O	sto	mon	x	x	x	x	x	x	
Santibañez-Aguilar et al. (2011)	O	det	mon/eco	x	x		x	x	x	
Schwaderer (2012)	O	det	mon	x	x				x	
Tittmann et al. (2010)	O	det	mon	x	x		x	x	x	
Walther et al. (2012)	O	det	mon	x	x	x	x		x	
You et al. (2012)	O	det	mon/eco/soc	x	x	x	x	x	x	
You and Wang (2011)	O	det	mon/eco	x	x	x	x	x	x	
Zamboni et al. (2009)	O	det	mon/eco	x	x	x	x			
Zhang and Hu (2013)	O	det	mon	x	x	x	x		x	

living beings as biomass, we have replaced the column “beings” with a new column “final products”. This column contains the entry “e” if electricity is the intended final product and “h” if heat is an intended final product. To ease readability, references allowing to also produce biofuel are marked with an additional “b”. An “f” indicates whether – besides electricity or heat – also fibre can be produced. However, the production of fibre will be discussed in more detail in Section 2.3.2.

Akgul et al. (2014) represent the co-firing of biomass with fossil fuels and a capturing and storage of CO_2 in a multi-objective, deterministic optimization model. The objectives are to minimize the total annual costs and the total annual emissions. All three stages of the the SC are covered with plants and residuals being possible feedstocks. Ayoub et al. (2007) offer decision support for a general, three-stage bioenergy SC. A geographical information system (GIS) and a simulation model help to estimate the potential biomass supply of wood and wood residuals and to identify promising locations of conversion facilities. Another simulation model is proposed by Caputo et al. (2005), which considers biomass-based energy generation through combustion and gasification facilities. The authors want to evaluate the effects of different logistical alternatives on the costs of conversion. The model does only comprise the first two stages of the SC. Information about possible biomass feedstocks is missing. Feng et al. (2010) investigate bio-refinery design within a three-stage forest product SC producing (woody) fibre, electricity and heat. A deterministic, multi-period optimization model maximizes the net present value of the SC, which is fed by wood and wood residuals.

Table 2.3: Literature concerning electricity and heat production

	O./S.	det./sto.	obj.	SC stages 1	2	3	biomass type plants	wood	resi.	final prod.
Akgul et al. (2014)	O	det	mon/eco	x	x	x	x		x	–/e/–/–
Aksoy et al. (2011)	O	det	mon		x			x	x	b/e/h/–
Ayoub et al. (2007)	S			x	x	x		x	x	–/e/–/–
Cambero et al. (2015)	O	det	mon	x	x	x			x	b/e/h/–
Caputo et al. (2005)	S			x	x					–/e/–/–
Feng et al. (2010)	O	det	mon	x	x	x		x	x	–/e/h/f
Frombo et al. (2009a)	O	det	mon	x	x	x		x	x	b/e/h/–
Frombo et al. (2009b)	O	det	mon	x	x	x	x	x	x	–/e/h/–
Judd et al. (2012)	O	det	mon	x						–/e/–/–
Lam et al. (2013)	O	det	mon	x					x	–/e/–/–
Meyer et al. (2015)	O	det	mon/eco	x	x		x	x		–/e/h/–
Meyer et al. (2016)	O	det	mon/eco	x	x		x		x	–/e/h/–
Paulo et al. (2015)	O	det	mon	x	x	x			x	–/e/–/–
Rauch and Gronalt (2011)	O	det	mon	x				x		–/e/h/–
Reche López et al. (2008)	O	det	mon	x	x			x	x	–/e/–/–
Rentizelas et al. (2009)	O	det	mon	x	x	x			x	–/e/h/–
Rentizelas and Tatsiopoulos (2010)	O	det	mon	x	x	x			x	–/e/h/–
Roni et al. (2014)	O	det	mon	x	x		x	x	x	–/e/–/–
Santibañez-Aguilar et al. (2011)	O	det	mon/eco	x	x		x	x	x	b/e/h/f
Tittmann et al. (2010)	O	det	mon	x	x		x	x	x	b/e/–/–
Wang et al. (2012)	O	det	mon	x	x		x			–/e/h/–

Frombo et al. (2009b) use a deterministic optimization model to produce energy and heat from woody biomass (plants, wood and residuals) in a three-stage SC. Its objective is to minimize the difference of the total costs (purchasing, transportation and plant costs) and the benefits deriving from energy sales. Judd et al. (2012) design a logistics system for bioenergy production, using satellite storage locations (SSLs). These SSLs are temporary and uncovered feedstock depots which are decentrally located around a biomass conversion facility. The autors' deterministic optimization model minimizes storage costs of the SSLs and transportation costs for only the first stage of a SC. Biomass is used as feedstock, but the type of biomass is not further specified. Lam et al. (2013) design the first stage of a green bioenergy SC basing on waste as feedstock. They propose a deterministic, two-stage optimization model, which maximizes the profit on a micro decision level and minimizes the costs on a macro decision level. First, the conversion processes of each conversion facility are optimized by choosing the best feedstock-to-product allocation (micro level). Then the whole SC is optimized by balancing supply and demand at minimal costs (macro level).

Meyer et al. (2015) and Meyer et al. (2016) combine the strategic and tactical planning of bioenergy and heat production in a two-stage SC. They introduce a basic, multi-objective, deterministic optimization model called OPTIMASS. Its objectives are to maximize the profits and energy outputs as well as to minimize the global warming potential. The model of the previous work from 2015 considers plants and wood as possible biomass feedstocks. The latter one considers plants and residuals. Paulo et al. (2015) use a deterministic optimization model to design a bioelectricity SC based on forestry residuals. Within the model the production capacities and locations are defined. They cover all three stages of the SC and consider several uncertainties by using sensitivity analysis. Minimizing the total SC costs is the single objective.

Rauch and Gronalt (2011) examine the relation between increasing energy costs and the transport mode choice in a forest fuel SC network, i.e., only woody biomass is considered as possible feedstock. Different modes of transport are analyzed to ensure the supply for combined heat and power plants. Therefore, only the first SC stage is covered. The objective of the presented deterministic optimization model is to minimize the total costs. Reche López et al. (2008) present a deterministic optimization model to determine locations and sizes of power facilities within a two-stage SC. They only focus on the supply side of the conversion facilities, which use wood and wood residuals as input. They apply particle swarm optimization to maximize a profitability index taking costs and benefits into consideration.

Rentizelas et al. (2009) support strategic decision making for residual-to-bioenergy conversion, more specifically for so-called "tri-generation applications" comprising electricity, heating and cooling. Their deterministic optimization model maximizes the net present value of a three-stage SC by choosing the optimal location for the biomass conversion facility, its size and the optimal mix of specific biomass residuals. Rentizelas and Tatsiopoulos (2010) optimize the locations of biomass-to-bioenergy conversion facilities producing electricity and heat for district energy applications. Their deterministic optimization model maximizes the net present value of a three-stage SC that is only fed by residuals. Roni et al. (2014) consider co-firing of biomass (plants, wood and residuals) in coal-fired power facilities. They propose a deterministic optimization model to design the first two stages of a SC as a hub-and-spoke structure. The model minimizes the costs of transport and investments in locations for a given energy demand. Finally, Wang et al. (2012) determine the supply of energy crops as well as the locations and capacities of conversion facilities generating heat and power. They propose a deterministic optimization model maximizing the profits of the two-stage SC.

As Table 2.3 shows, again optimization models are preferred to simulation models. Only a single "pure" simulation model has been proposed. Similarly to the last section, there are only a few multi-objective models. Three references do only consider a single-stage SC, two of them concentrating on the biomass supply, one of them on the biomass conversion. Most references comprise either the first two or all three stages of the SC. Not surprisingly, the variety of biomass used is similar to biofuel production. As mentioned before, heat could be produced without generating electricity. However, none of the references found intends to do this.

2.3.2 Fibre

Table 2.4 summarizes literature on the quantitative, strategic planning of biomass-based SCs that aims at producing final products of (at least) the fibre group. Again we will only discuss references in detail, which have not yet been introduced in the preceding sections.

Table 2.4: Literature concerning fibre production

				SC stages			biomass type			final
	O./S.	det./sto.	obj.	1	2	3	plants	wood	resi.	prod.
Bowling et al. (2011)	O	det	mon	x	x					b/–/–/f
Chen and Fan (2012)	O	sto	mon	x	x	x			x	b/–/–/f
Correll et al. (2014)	O/S	det	mon	x			x			b/–/–/f
Ekşioğlu et al. (2009)	O	det	mon	x	x		x	x	x	b/–/–/f
Feng et al. (2010)	O	det	mon	x	x	x		x	x	–/e/h/f
Gunn (2009)	O	det	mon	x				x		–/–/–/f
Gunnarsson et al. (2005)	O	det	mon			x				–/–/–/f
Kelley et al. (2013)	O	det	mon	x						–/–/–/f
Philpott and Everett (2001)	O	det	mon	x	x	x		x		–/–/–/f
Santibañez-Aguilar et al. (2011)	O	det	mon/eco	x	x		x	x	x	b/e/h/f
Schwaderer (2012)	O	det	mon	x	x				x	b/–/–/f
Troncoso and Garrido (2005)	O	det	mon	x	x			x		–/–/–/f

Gunn (2009) describes an optimization model to produce forest products. Just the first SC stage is considered with wood being the only feedstock. As only the first stage of the SC is considered, no information about specific forest products is given. The developed optimization model is deterministic with the objective to maximize the profits. Gunnarsson et al. (2005) integrate the search for terminal locations of various pulp products and for their outbound shipping routes in a deterministic optimization model minimizing total distribution costs. Thus only the third SC stage, downstream of some pulp mills in Scandinavia, is considered. Specific information on biomass feedstocks is missing, but pulp mills are usually fed by forest wood.

Kelley et al. (2013) design a transportation network in a mainly roadless region of Amazonian Ecuador in order to transport indigenous goods to the markets. A deterministic optimization model minimizes the total costs of storage and of the various transportation vehicles. Only the first stage of the SC is considered. The types of biomass feedstocks are not mentioned. Philpott and Everett (2001) optimize an SC of the paper industry. They propose a deterministic optimization model to allocate suppliers to paper mills and customers and their requested products to paper machines, respectively. The objective is to maximize the overall profits of the three-stage, wood-based SC. Troncoso and Garrido (2005) deterministically minimize the costs of the production and logistics processes of a forest SC by choosing the optimal location and size of conversion facilities. Additionally, they consider production quantities and freight flows. Wood is the only feedstock. Specific information on the final items is missing because the authors do only consider the first two stages of such SCs.

Note that there is a whole stream of literature on quantitative (and also strategic) SC planning in the pulp and paper industry. The respective references discussed above are only a few typical examples. As mentioned in Section 2.2.2.2, including all relevant work would have led to a loss of focus on more innovative types of biomass-based SCs.

According to Table 2.4 again optimization models are dominating. Moreover, only a single stochastic and a single multi-objective model can be found. The fibre research rather concentrates on the upstream instead of downstream part of the SC. Despite of that, information on the type of biomass used is more often missing. No research has been identified, which intends to exclusively produce non-wood based fibres like chemicals, pharmaceuticals or tensides.

2.4 Conclusions

All in all, when comparing Tables 2.2, 2.3 and 2.4, we recognize that most research has been done on biofuel production, whereas electricity, heat and fibre production have less frequently been considered. However, the research effort in biofuel SCs seems to be decreasing. The peak in the number of published articles was in 2011. In contrast, the effort in biomass-based electricity and heat SCs as well as in fibre SCs is relatively stable since 2009, yet on a much lower level. Thus, the overall research effort on the strategic planning of biomass-based SCs appears rather decreasing. Overall, deterministic optimization models, deciding about the structure and facilities of a two- to three-stage supply chain starting from the biomass supply, are dominating. Usually they pursue only a single monetary objective, which is to either minimize costs or maximize profits. In multi-period models, which do not only determine the type of investment, but also the timing of investments, net present values are taken into account. Except for living beings (which rather play a role in food SCs), all types of biomass are considered – often even simultaneously as substitutable or supplementary feedstocks. However, it seems that research during the years 2011 and 2012 focused stronger on plants-based fuel and fibre SCs, whereas earlier on and later on wood- and residual-feedstocks appealed higher interest.

Figures 2.3 and 2.4 of Section 2.2 have revealed that many different participants may be involved in three-stage, biomass-based supply chains. However, none of the models of Section 2.3 takes an inter-organizational perspective, caring about problems concerning the cooperation between legally separate companies (e.g., trust building, aligning incentives or sharing of information, risks, joint profits or joint costs). The vast majority of the models is characterized by a centralized point of view, meaning that the decision maker is a centralized SC planner in an intra-organizational SC, having all necessary information about the SC (i.e., deterministic model) and being able to decide for the supply chain as a whole. Sometimes this planner is characterized by a rather macroeconomic point of view, considering influences on the economy as a whole like environmental or social aspects (for instance, see the multi-objective models and simulation models). Apart from those, there are some models with a conversion facility owner's point of view or with a farmer's or third-party logistics service provider's point of view. The SC stages depicted in Tables 2.2–2.4 give a hint on the specific decision maker: If all three stages are considered, this indicates the planning of the whole SC from a central SC planner's point of view. Exceptions are models on the planning of a single biorefinery with both upstream and downstream stages. A partial consideration indicates either again the biorefinery operator's point of view (if only the second stage is considered) or the farmer's and third-party logistics service provider's point of view, respectively.

Comparing biomass-based SCs with their traditional fossil-based counterparts helps to stress further specific characteristics of the models of Section 2.3.

Fossil-based fuel is produced in a few, large refineries of mineral oil companies (Roitsch and Meyr, 2015). The only input material "crude oil" may show a different chemical composition if it stems from different oil fields in different regions of the world. Nevertheless, as compared to biomass, it is a very homogeneous material. By using pipelines or tankers, this raw material can cost-efficiently be transported to the refineries. The refineries are of industrial size, what also allows cost-efficient conversion processes. If used as automotive fuel, merely the distribution from the refineries to the multitude of petrol stations requires small-sized transports by trucks. Storage is possible at any stage of the supply chain. It is necessary to save costs (e.g., varying market prices for crude oil, lotsizing) in and hedge against risks (e.g., varying lead times) of transportation and production.

As opposite, biomass feedstocks are typically more heterogeneous. They are decentrally located within a specific region and have there to be collected or harvested. The biomass shows a high content of water and a low energy density. If it should also be brought to a few, centrally located conversion facilities, either high transportation costs would result or a further, decentral (pre-) processing step would be necessary, which increases the energy density and thus decreases transportation costs. However, this pre-processing may also incur fix costs for investments and variable costs for transformation. Some types of biomass are perishable (e.g., plants). That means, either decentral pre-processing additionally conserves the biomass so that it can be stored. Or it has – more or less immediately – to be transported to the central conversion facilities. For other types of biomass (e.g., wood), decentral storage may even save a costly pre-processing step (like drying). Anyway, decisions concerning the number, locations and capacities of (pre-)processing facilities for *biofuel* have to be made by managing the tradeoff between, at least, investment costs for these facilities and transportation costs of unprocessed biomass. Potential solutions, provided in the analyzed literature, are to use only one central conversion facility, several centralized conversion facilities, or central conversion facilities and several upstream, decentral pre-processing facilities. The decision about these potential network structures is crucially dependent on the scalability of the conversion facilities, which are also denoted as "biorefineries". From a transformation point of view, biorefineries for biofuel production play a similar role as petroleum refineries. However, the characteristics of the used supply are totally different.

Examples for many decentral conversion facilities can also be found, but rather for the production of electricity and heat. Whereas typical *fossil-based power plants* either also profit from cost-efficient transportation means (pipelines) for their supplying material (natural gas) or are located in a region of highly concentrated supply (coal), *biogas refineries* usually are decentrally located and small-sized. To save transportation costs, they can only cost-efficiently be fed by biomass from their immediate vicinity. Their small-sized conversion technology is currently only profitable if subsidies are guaranteed by law. The main advantage of this type of biomass-based supply chain is that its primary final product "electricity" can easily and cheaply be brought to the final consumer by feeding it into the already existing power network. Unfortunately, its co-product "heat" cannot as easily be transported. Thus, a clever usage has to be found, for example, through cooperations with neighboring industrial parks, close-by housing areas etc. Intra-organizational decisions about locations of (pre-)processing facilities are less important here. At most, investments in alternative conversion technologies and facility designs could be optimized. Overall, however, it is rather necessary to establish successful regional, inter-organizational cooperations between suppliers of biomass, operators of the biogas refinery and adjacent consumers of heat. As Section 2.3.1.2 has shown, SCM research does not yet offer much support for this.

Supply chains producing fibres like chemicals, tensides and pharmaceuticals from biomass compete with traditional fossil-based (natural gas, coal, crude oil) SCs of the chemical and pharmaceutical industries. *Fossil-based* *(organic) chemicals* usually are produced on an industrial scale in integrated production sites consisting of several production facilities which are interconnected by a pipeline system. They are supplied by the mineral oil industry with large quantities of intermediate materials like Naphtha that results as a by-product of typical refinery processes (see above). These fossil intermediate materials are split into basic chemicals, which are re-composed into intermediate chemicals so that both can finally react to final chemicals (Kirschstein, 2015, Chap. 2). In order to save transportation costs, chemical production sites are often located in close vicinity to oil refineries. Thus they also profit from economies of scale in transportation and production. In contrast, *biomass-based fibre SCs* struggle with the same problems as biomass-based fuel SCs. Bioethanol could play a similar role for biomass-based fibre SCs as Naphtha does for fossil-based SCs. It can already be produced on an industrial scale. For example, the PlantBottle™, a beverage bottle developed and used by the Coca-Cola Company, is partly made out of bioethanol, which is produced on large scale from sugarcane of Brazil (Coca-Cola, 2016). However, for the reasons mentioned above, this is currently more costly than using fossils as an input. Small-scaled biorefineries, which could – similarly to biogas refineries – process the biomass decentrally into bioethanol or even into final products of the fibre type are still too expensive for an operational usage. Since it is not yet clear what technological research will bring, research on the strategic planning of such types of SCs appears premature.

As already mentioned, SCs for pulp and paper and other wood-based fibres traditionally already base on biomass as source material. The same is, of course, true for food production. Therefore, much research has already been done to find out how to place conversion facilities into these types of SCs. Examples are given by Carlsson et al. (2009), Cambero and Sowlati (2014) or Ahumada and Villalobos (2009). It can be learned that especially the upstream processes in biomass-based SCs are characterized by manifold uncertainties. For instance, the quality and quantity of biomass supply is depending on the weather and thus uncertain. Moreover, the harvesting or collection time may be seasonal and uncertain, too. Hence, the upstream processes, meaning the supply side of the SC, are characteristic and crucial for many of the downstream processes. Due to the seasonal and uncertain supply, storage would be desired. However, if the biomass is perishable, this may hardly be possible (e.g., for fresh food) or (pre-)processing steps are necessary to enlarge durability. As Section 2.3 has shown, some of the models for the more innovative fuel and fibre SCs tackle the same problems. They deal with uncertainty by using stochastic modeling techniques. Here, typically the biomass supply is modeled as being uncertain. Additionally, the demand is uncertain, too, in some of the models. Perishability is less in the focus than it is in food SCs (see, e.g., Amorim et al. (2013)). It is rather indirectly considered by potentially introducing pre-processing facilities.

2.5 Summary and outlook

This chapter provided an overview of the latest literature on the long-term, strategic planning of biomass-based supply chains using quantitative models of operations research. We structured the overall research field "bioeconomy" by means of various utilization pathways of biomass. In such utilization pathways, the scarce resource "biomass", i.e., the ultimate supply, is the starting point. In contrast, supply chains are rather demand- than supply-oriented. All participants in an SC cooperate to fulfill the final customer's demand. Section 2.2 bridged the gap between the demand-oriented view of SC management models and the supply-oriented view of bioeconomy. Subsequently, several dozen publications have been analyzed with respect to the modeling characteristics used, the sections of the SC covered and the types of biomass considered.

As results of and conclusions from the analysis, some characteristics of biomass-based SCs, some trends of current research on the strategic planning of biomass-based SCs and some research gaps have been identified. On the one hand, it is noticeable that the research effort on the strategic planning of SCs producing fuels and rather "innovative" fibres from biomass seems to be decreasing. This is caused by a decrease of research on biofuel production. Overall, peak efforts were recorded in the years 2011 and 2012, research thereby mainly focusing on plants-based biomass. On the other hand, the following characteristics of biomass-based SCs have been identified: Biomass-based SCs are inter-organizational and characterized by a great heterogeneity of parties involved. This heterogeneity should be tackled by means of inter-organizational cooperation and intra-organizational coordination. However, most of the analyzed models assume an intra-organizational view with a central, omniscient and omnipotent planner. High uncertainty concerning the biomass supply is another important characteristic of biomass-based SCs, which is considered by some models. High transportation costs of unprocessed biomass, caused by its high water content and low energy density, are a further characteristic. Because of them, decisions on locations for pre-processing and conversion facilities are crucial and thus considered by most of the analyzed models.

Further research should also take inter-organizational aspects of SC management into account. Biomass-based SCs have to become profitable on their own, i.e., without governmental subsidies, and have to compete with their fossil-based counterparts. Clever cooperation between the partners of biomass-based SCs would help to save costs and to become more competitive. Nevertheless, the current intra-organizational models with a central view are not useless. They can serve as a benchmark of what could be achieved if an SC would be truly integrated. Thus these models need to be brought as close to reality as possible, for example, by increasingly incorporating the risks arising through supply and demand uncertainties. And they permanently need to be adapted to new surrounding constraints, which, for instance, emerge from new laws or changed governmental support programs.

Bibliography

Ahn, Y.C., Lee, I.B., Lee, K.H., Han, J.H., 2015. Strategic planning design of microalgae biomass-to-biodiesel supply chain network: Multi-period deterministic model. Applied Energy 154, 528–542. doi:10.1016/j.apenergy.2015.05.047.

Ahumada, O., Villalobos, J.R., 2009. Application of planning models in the agri-food supply chain: A review. European Journal of Operational Research 196, 1–20. doi:10.1016/j.ejor.2008.02.014.

Akgul, O., Mac Dowell, N., Papageorgiou, L.G., Shah, N., 2014. A mixed integer nonlinear programming (MINLP) supply chain optimisation framework for carbon negative electricity generation using biomass to energy with CCS (BECCS) in the UK. International Journal of Greenhouse Gas Control 28, 189–202. doi:10.1016/j.ijggc.2014.06.017.

Akgul, O., Shah, N., Papageorgiou, L.G., 2012a. Economic optimisation of a UK advanced biofuel supply chain. Biomass and Bioenergy 41, 57–72. doi:10.1016/j.biombioe.2012.01.040.

Akgul, O., Shah, N., Papageorgiou, L.G., 2012b. An optimisation framework for a hybrid first/second generation bioethanol supply chain. Computers & Chemical Engineering 42, 101–114. doi:10.1016/j.compchemeng.2012.01.012.

Akgul, O., Zamboni, A., Bezzo, F., Shah, N., Papageorgiou, L.G., 2011. Optimization-based approaches for bioethanol supply chains. Industrial & Engineering Chemistry Research 50, 4927–4938. doi:10.1021/ie101392y.

Akkerman, R., Farahani, P., Grunow, M., 2010. Quality, safety and sustainability in food distribution: A review of quantitative operations management approaches and challenges. OR Spectrum 32, 863–904. doi:10.1007/s00291-010-0223-2.

Aksoy, B., Cullinan, H., Webster, D., Gue, K., Sukumaran, S., Eden, M., Sammons, N., 2011. Woody biomass and mill waste utilization opportunities in Alabama: Transportation cost minimization, optimum facility location, economic feasibility, and impact. Environmental Progress & Sustainable Energy 30, 720–732. doi:10.1002/ep.10501.

Amorim, P., Meyr, H., Almeder, C., Almada-Lobo, B., 2013. Managing perishability in production-distribution planning: a discussion and review. Flexible Services and Manufacturing Journal , 1–25.

An, H., Wilhelm, W.E., Searcy, S.W., 2011a. A mathematical model to design a lignocellulosic biofuel supply chain system with a case study based on a region in Central Texas. Bioresource Technology 102, 7860–7870. doi:10.1016/j.biortech.2011.05.060.

An, H., Wilhelm, W.E., Searcy, S.W., 2011b. Biofuel and petroleum-based fuel supply chain research: A literature review. Biomass and Bioenergy 35, 3763–3774. doi:10.1016/j.biombioe.2011.06.021.

Andersen, F., Iturmendi, F., Espinosa, S., Diaz, M.S., 2012. Optimal design and planning of biodiesel supply chain with land competition. Computers & Chemical Engineering 47, 170–182. doi:10.1016/j.compchemeng.2012.06.044.

Awudu, I., Zhang, J., 2012. Uncertainties and sustainability concepts in biofuel supply chain management: A review. Renewable and Sustainable Energy Reviews 16, 1359–1368. doi:10.1016/j.rser.2011.10.016.

Ayoub, N., Martins, R., Wang, K., Seki, H., Naka, Y., 2007. Two levels decision system for efficient planning and implementation of bioenergy production. Energy Conversion and Management 48, 709–723. doi:10.1016/j.enconman.2006.09.012.

Ba, B.H., Prins, C., Prodhon, C., 2015. Models for optimization and performance evaluation of biomass supply chains: An Operations Research perspective. Renewable Energy doi:10.1016/j.renene.2015.07.045.

Bai, Y., Hwang, T., Kang, S., Ouyang, Y., 2011. Biofuel refinery location and supply chain planning under traffic congestion. Transportation Research Part B: Methodological 45, 162–175. doi:10.1016/j.trb.2010.04.006.

Bernardi, A., Giarola, S., Bezzo, F., 2013. Spatially explicit multiobjective optimization for the strategic design of first and second generation biorefineries including carbon and water footprints. Industrial & Engineering Chemistry Research 52, 7170–7180. doi:10.1021/ie302442j.

Bioökonomierat (Ed.), 2015. Nachhaltige Bereitstellung von biobasierten agrarischen Rohstoffen. Office of the Bioeconomy Council.

BMBF, BMEL, 2014. Bioökonomie in Deutschland: Chancen für eine biobasierte nachhaltige Zukunft.

Bowling, I.M., Ponce-Ortega, J.M., El-Halwagi, M.M., 2011. Facility location and supply chain optimization for a biorefinery. Industrial & Engineering Chemistry Research 50, 6276–6286. doi:10.1021/ie101921y.

Cambero, C., Sowlati, T., 2014. Assessment and optimization of forest biomass supply chains from economic, social and environmental perspectives – a review of literature. Renewable and Sustainable Energy Reviews 36, 62–73. doi:10.1016/j.rser.2014.04.041.

Cambero, C., Sowlati, T., Marinescu, M., Röser, D., 2015. Strategic optimization of forest residues to bioenergy and biofuel supply chain. International Journal of Energy Research 39, 439–452. doi:10.1002/er.3233.

Caputo, A.C., Palumbo, M., Pelagagge, P.M., Scacchia, F., 2005. Economics of biomass energy utilization in combustion and gasification plants: effects of logistic variables. Biomass and Bioenergy 28, 35–51. doi:10.1016/j.biombioe.2004.04.009.

Carlsson, D., D'Amours, S., Martel, A., Rönnqvist, M., 2009. Supply chain planning models in the pulp and paper industry. INFOR 47, 167–183. doi:10.3138/infor.47.3.167.

Chen, C.W., Fan, Y., 2012. Bioethanol supply chain system planning under supply and demand uncertainties. Transportation Research Part E: Logistics and Transportation Review 48, 150–164. doi:10.1016/j.tre.2011.08.004.

Christopher, M., 2005. Logistics and supply chain management, creating value-adding networks. 3 ed., Financial Times Prentice Hall, Harlow.

Cobuloglu, H.I., Büyüktahtakın, Esra, İ., 2014. A mixed-integer optimization model for the economic and environmental analysis of biomass production. Biomass and Bioenergy 67, 8–23. doi:10.1016/j.biombioe.2014.03.025.

Coca-Cola, 2016. PlantBottle Frequently Asked Questions: The Coca-Cola Company. URL: http://www.coca-colacompany.com/stories/plantbottle-frequently-asked_questions/. accessed 2016-02-26.

Correll, D., Suzuki, Y., Martens, B.J., 2014. Logistical supply chain design for bioeconomy applications. Biomass and Bioenergy 66, 60–69. doi:10.1016/j.biombioe.2014.03.036.

Corsano, G., Vecchietti, A.R., Montagna, J.M., 2011. Optimal design for sustainable bioethanol supply chain considering detailed plant performance model. Computers & Chemical Engineering 35, 1384–1398. doi:10.1016/j.compchemeng.2011.01.008.

Dabbene, F., Gay, P., Tortia, C., 2014. Traceability issues in food supply chain management: A review. Biosystems Engineering 120, 65–80. doi:10.1016/j.biosystemseng.2013.09.006.

Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), 2017. Knowledge-driven developments in the bioeconomy. Economic complexity and evolution, Springer Verlag, Cham.

Dal-Mas, M., Giarola, S., Zamboni, A., Bezzo, F., 2011. Strategic design and investment capacity planning of the ethanol supply chain under price uncertainty. Biomass and Bioenergy 35, 2059–2071. doi:10.1016/j.biombioe.2011.01.060.

De Mol, R.M., Jogems, M. A. H., Beek, P.V., Gigler, J.K., 1997. Simulation and optimization of the logistics of biomass fuel collection. Netherlands Journal of Agricultural Science 45, 219–228.

Diepenbrock, W., 2014. Nachwachsende Rohstoffe. volume 4189 of *UTB*. Ulmer, Stuttgart.

Dunnett, A.J., Adjiman, C.S., Shah, N., 2008. A spatially explicit whole-system model of the lignocellulosic bioethanol supply chain: an assessment of decentralised processing potential. Biotechnology for biofuels 1, 13–30. doi:10.1186/1754-6834-1-13.

Ekşioğlu, S., Li, S., Zhang, S., Sokhansanj, S., Petrolia, D., 2010. Analyzing impact of intermodal facilities on design and management of biofuel supply chain. Transportation Research Record: Journal of the Transportation Research Board 2191, 144–151. doi:10.3141/2191-18.

Ekşioğlu, S.D., Acharya, A., Leightley, L.E., Arora, S., 2009. Analyzing the design and management of biomass-to-biorefinery supply chain. Computers & Industrial Engineering 57, 1342–1352. doi:10.1016/j.cie.2009.07.003.

Feng, Y., D'Amours, S., LeBel, L., Nourelfath, M., 2010. Integrated bio-refinery and forest products supply chain network design using mathematical programming approach. CIRRELT 2010.

Fichtner, S., Meyr, H., 2017. Strategic Supply Chain Planning in Biomass-Based Industries: A Literature Review of Quantitative Models, in: Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), Knowledge-driven developments in the bioeconomy. Springer Verlag, Cham. Economic complexity and evolution, pp. 259–291.

Fleischmann, B., Meyr, H., 2003. Planning hierarchy, modeling and advanced planning systems, in: De Kok, A., Graves, S.C. (Eds.), Supply Chain Management: Design, Coordination, Operation. Elsevier, Amsterdam et al.. volume 11 of *Handbooks in Operations Research and Management Science*. chapter 9, pp. 457–523.

Fleischmann, B., Meyr, H., Wagner, M., 2015. Advanced planning, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 71–95. doi:10.1007/978-3-642-55309-7_4.

Frombo, F., Minciardi, R., Robba, M., Rosso, F., Sacile, R., 2009a. Planning woody biomass logistics for energy production: A strategic decision model. Biomass and Bioenergy 33, 372–383. doi:10.1016/j.biombioe.2008.09.008.

Frombo, F., Minciardi, R., Robba, M., Sacile, R., 2009b. A decision support system for planning biomass-based energy production. Energy 34, 362–369. doi:10.1016/j.energy.2008.10.012.

Giarola, S., Bezzo, F., Shah, N., 2013. A risk management approach to the economic and environmental strategic design of ethanol supply chains. Biomass and Bioenergy 58, 31–51. doi:10.1016/j.biombioe.2013.08.005.

Giarola, S., Zamboni, A., Bezzo, F., 2011. Spatially explicit multi-objective optimisation for design and planning of hybrid first and second generation biorefineries. Computers & Chemical Engineering 35, 1782–1797. doi:10.1016/j.compchemeng.2011.01.020.

Giarola, S., Zamboni, A., Bezzo, F., 2012. Environmentally conscious capacity planning and technology selection for bioethanol supply chains. Renewable Energy 43, 61–72. doi:10.1016/j.renene.2011.12.011.

Gunn, E., 2009. Some perspectives on strategic forest management models and the forest products supply chain. INFOR 47, 261–272. doi:10.3138/infor.47.3.261.

Gunnarsson, H., Rönnqvist, M., Carlsson, D., 2005. A combined terminal location and ship routing problem. Journal of the Operational Research Society 57, 928–938. doi:10.1057/palgrave.jors.2602057.

Huang, Y., Chen, C.W., Fan, Y., 2010. Multistage optimization of the supply chains of biofuels. Transportation Research Part E: Logistics and Transportation Review 46, 820–830. doi:10.1016/j.tre.2010.03.002.

Ivanov, B., Stoyanov, S., 2016. A mathematical model formulation for the design of an integrated biodiesel-petroleum diesel blends system. Energy 99, 221–236. doi:10.1016/j.energy.2016.01.038.

Judd, J.D., Sarin, S.C., Cundiff, J.S., 2012. Design, modeling, and analysis of a feedstock logistics system. Bioresource Technology 103, 209–218. doi:10.1016/j.biortech.2011.09.111.

Kaltschmitt, M., 2009. Biomasse als nachwachsender Energieträger, in: Kaltschmitt, M., Hartmann, H., Hofbauer, H. (Eds.), Energie aus Biomasse: Grundlagen, Techniken und Verfahren. 2 ed.. Springer Berlin Heidelberg, Berlin, Heidelberg. chapter 1.1, pp. 1–7.

Kanzian, C., 2009. Regional energy wood logistics – optimizing local fuel supply. Silva Fennica 43, 113–128.

Kelley, J., Kuby, M., Sierra, R., 2013. Transportation network optimization for the movement of indigenous goods in Amazonian Ecuador. Journal of Transport Geography 28, 89–100. doi:10.1016/j.jtrangeo.2012.11.006.

Kim, J., Realff, M.J., Lee, J.H., 2011a. Optimal design and global sensitivity analysis of biomass supply chain networks for biofuels under uncertainty. Computers & Chemical Engineering 35, 1738–1751. doi:10.1016/j.compchemeng.2011.02.008.

Kim, J., Realff, M.J., Lee, J.H., Whittaker, C., Furtner, L., 2011b. Design of biomass processing network for biofuel production using an MILP model. Biomass and Bioenergy 35, 853–871. doi:10.1016/j.biombioe.2010.11.008.

Kirschstein, T., 2015. Integrated Planning of Chemical Supply Chains. Springer Fachmedien Wiesbaden.

Lam, H.L., Ng, W.P., Ng, R.T., Ng, E.H., Aziz, Mustafa K. Abdul, Ng, D.K., 2013. Green strategy for sustainable waste-to-energy supply chain. Energy 57, 4–16. doi:10.1016/j.energy.2013.01.032.

Leão, R., Hamacher, S., Oliveira, F., 2011. Optimization of biodiesel supply chains based on small farmers: A case study in Brazil. Bioresource Technology 102, 8958–8963. doi:10.1016/j.biortech.2011.07.002.

Leduc, S., Lundgren, J., Franklin, O., Dotzauer, E., 2010. Location of a biomass based methanol production plant: A dynamic problem in northern Sweden. Applied Energy 87, 68–75. doi:10.1016/j.apenergy.2009.02.009.

Leduc, S., Schwab, D., Dotzauer, E., Schmid, E., Obersteiner, M., 2008. Optimal location of wood gasification plants for methanol production with heat recovery. International Journal of Energy Research 32, 1080–1091. doi:10.1002/er.1446.

Lin, T., Rodríguez, L.F., Shastri, Y.N., Hansen, A.C., Ting, K.C., 2014. Integrated strategic and tactical biomass-biofuel supply chain optimization. Bioresource Technology 156, 256–266. doi:10.1016/j.biortech.2013.12.121.

Marufuzzaman, M., Eksioglu, S.D., Huang, Y., 2014. Two-stage stochastic programming supply chain model for biodiesel production via wastewater treatment. Computers & Operations Research 49, 1–17. doi:10.1016/j.cor.2014.03.010.

Marvin, W., Schmidt, L.D., Benjaafar, S., Tiffany, D.G., Daoutidis, P., 2012. Economic optimization of a lignocellulosic biomass-to-ethanol supply chain. Chemical Engineering Science 67, 68–79. doi:10.1016/j.ces.2011.05.055.

Marvin, W., Schmidt, L.D., Daoutidis, P., 2013. Biorefinery location and technology selection through supply chain optimization. Industrial & Engineering Chemistry Research 52, 3192–3208. doi:10.1021/ie3010463.

Mele, F.D., Kostin, A.M., Guillén-Gosálbez, G., Jiménez, L., 2011. Multiobjective Model for More Sustainable Fuel Supply Chains. A Case Study of the Sugar Cane Industry in Argentina. Industrial & Engineering Chemistry Research 50, 4939–4958. doi:10.1021/ie101400g.

Meyer, A.d., Cattrysse, D., van Orshoven, J., 2015. A generic mathematical model to optimise strategic and tactical decisions in biomass-based supply chains (OPTIMASS). European Journal of Operational Research 245, 247–264. doi:10.1016/j.ejor.2015.02.045.

Meyer, A.d., Cattrysse, D., van Orshoven, J., 2016. Considering biomass growth and regeneration in the optimisation of biomass supply chains. Renewable Energy 87, 990–1002. doi:10.1016/j.renene.2015.07.043.

Mohseni, S., Pishvaee, M.S., 2016. A robust programming approach towards design and optimization of microalgae-based biofuel supply chain. Computers & Industrial Engineering 100, 58–71. doi:10.1016/j.cie.2016.08.003.

Mohseni, S., Pishvaee, M.S., Sahebi, H., 2016. Robust design and planning of microalgae biomass-to-biodiesel supply chain: A case study in iran. Energy 111, 736–755. doi:10.1016/j.energy.2016.06.025.

Osmani, A., Zhang, J., 2013. Stochastic optimization of a multi-feedstock lignocellulosic-based bioethanol supply chain under multiple uncertainties. Energy 59, 157–172. doi:10.1016/j.energy.2013.07.043.

Paulo, H., Azcue, X., Barbosa-Póvoa, A.P., Relvas, S., 2015. Supply chain optimization of residual forestry biomass for bioenergy production: The case study of Portugal. Biomass and Bioenergy 83, 245–256. doi:10.1016/j.biombioe.2015.09.020.

Philpott, A., Everett, G., 2001. Supply chain optimisation in the paper industry. Annals of Operations Research 108, 225–237. doi:10.1023/A:1016071331034.

Rauch, P., Gronalt, M., 2011. The effects of rising energy costs and transportation mode mix on forest fuel procurement costs. Biomass and Bioenergy 35, 690–699. doi:10.1016/j.biombioe.2010.10.015.

Reche López, P., Jurado, F., Ruiz Reyes, N., García Galán, S., Gómez, M., 2008. Particle swarm optimization for biomass-fuelled systems with technical constraints. Engineering Applications of Artificial Intelligence 21, 1389–1396. doi:10.1016/j.engappai.2008.04.013.

Rentizelas, A.A., Tatsiopoulos, I.P., 2010. Locating a bioenergy facility using a hybrid optimization method. International Journal of Production Economics 123, 196–209. doi:10.1016/j.ijpe.2009.08.013.

Rentizelas, A.A., Tatsiopoulos, I.P., Tolis, A., 2009. An optimization model for multi-biomass tri-generation energy supply. Biomass and Bioenergy 33, 223–233. doi:10.1016/j.biombioe.2008.05.008.

Roitsch, M., Meyr, H., 2015. Oil industry, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 443–458. doi:10.1007/978-3-642-55309-7_24.

Roni, M., Eksioglu, S.D., Searcy, E., Jha, K., 2014. A supply chain network design model for biomass co-firing in coal-fired power plants. Transportation Research Part E: Logistics and Transportation Review 61, 115–134. doi:10.1016/j.tre.2013.10.007.

Santibañez-Aguilar, J.E., González-Campos, J.B., Ponce-Ortega, J.M., Serna-González, M., El-Halwagi, M.M., 2011. Optimal planning of a biomass conversion system considering economic and environmental aspects. Industrial & Engineering Chemistry Research 50, 8558–8570. doi:10.1021/ie102195g.

Schwaderer, F., 2012. Integrierte Standort-, Kapazitäts- und Technologieplanung von Wertschöpfungsnetzwerken zur stofflichen und energetischen Biomassenutzung. Dissertation. Karlsruher Institut für Technologie. Karlsruhe.

Soysal, M., Bloemhof-Ruwaard, J.M., Meuwissen, M., van der Vorst, J., 2012. A review on quantitative models for sustainable food logistics management. International Journal of Foord System Dynamics 3, 136–155.

Stadtler, H., 2015. Supply Chain Management – An Overview, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 3–28. doi:10.1007/978-3-642-55309-7_1.

Thrän, D., Scholwin, F., Körner, I., 2009. Sonstige Biomasse, in: Kaltschmitt, M., Hartmann, H., Hofbauer, H. (Eds.), Energie aus Biomasse: Grundlagen, Techniken und Verfahren. 2 ed.. Springer Berlin Heidelberg, Berlin, Heidelberg. chapter 4.3, pp. 157–171.

Tittmann, P.W., Parker, N.C., Hart, Q.J., Jenkins, B.M., 2010. A spatially explicit techno-economic model of bioenergy and biofuels production in California. Journal of Transport Geography 18, 715–728. doi:10.1016/j.jtrangeo.2010.06.005.

Troncoso, J.J., Garrido, R.A., 2005. Forestry production and logistics planning: an analysis using Mixed-Integer Programming. Forest Policy and Economics 7, 625–633. doi:10.1016/j.forpol.2003.12.002.

Tsolakis, N.K., Keramydas, C.A., Toka, A.K., Aidonis, D.A., Iakovou, E.T., 2014. Agrifood supply chain management: A comprehensive hierarchical decision-making framework and a critical taxonomy. Biosystems Engineering 120, 47–64. doi:10.1016/j.biosystemseng.2013.10.014.

Türk, O., 2014. Stoffliche Nutzung nachwachsender Rohstoffe: Grundlagen - Werkstoffe - Anwendungen. Springer Vieweg, Wiesbaden.

Walther, G., Schatka, A., Spengler, T.S., 2012. Design of regional production networks for second generation synthetic bio-fuel – A case study in Northern Germany. European Journal of Operational Research 218, 280–292. doi:10.1016/j.ejor.2011.09.050.

Wang, S., Hastings, A., Smith, P., 2012. An optimization model for energy crop supply. GCB Bioenergy 4, 88–95. doi:10.1111/j.1757-1707.2011.01112.x.

World Bank, 2015. World development indicators: Growth of output. URL: http://wdi.worldbank.org/table/4.1. accessed 2016-02-15.

You, F., Tao, L., Graziano, D.J., Snyder, S.W., 2012. Optimal design of sustainable cellulosic biofuel supply chains: Multiobjective optimization coupled with life cycle assessment and input-output analysis. AIChE Journal 58, 1157–1180. doi:10.1002/aic.12637.

You, F., Wang, B., 2011. Life cycle optimization of biomass-to-liquid supply chains with distributed–centralized processing networks. Industrial & Engineering Chemistry Research 50, 10102–10127. doi:10.1021/ie200850t.

Zamboni, A., Shah, N., Bezzo, F., 2009. Spatially explicit static model for the strategic design of future bioethanol production systems. 1. cost Minimization. Energy & Fuels 23, 5121–5133. doi:10.1021/ef900456w.

Zhang, L., Hu, G., 2013. Supply chain design and operational planning models for biomass to drop-in fuel production. Biomass and Bioenergy 58, 238–250. doi:10.1016/j.biombioe.2013.08.016.

Zhang, W., Wilhelm, W.E., 2011. OR/MS decision support models for the specialty crops industry: a literature review. Annals of Operations Research 190, 131–148. doi:10.1007/s10479-009-0626-0.

3 Biogas plant optimization by increasing its flexibility considering uncertain revenues

Abstract[3] Increasing shares of volatile energy resources like wind and solar energy will require flexibly schedulable energy resources to compensate for their volatility. Biogas plants can produce their energy flexibly and on demand, if their design is adjusted adequately. In order to achieve a flexibly schedulable biogas plant, the design of this plant has to be adapted to decouple the biogas and electricity production. Therefore, biogas storage possibilities and additional electrical capacity are necessary. The investment decision about the size of the biogas storage and the additional electrical capacity depends on the fluctuation of energy market prices and the availability of governmental subsidies. This work presents an approach supporting investment decisions to increase the flexibility of a biogas plant by installing gas storages and additional electrical capacities under consideration of revenues out of direct marketing at the day-ahead market. In order to support the strategic, long-term investment decisions, an operative plant schedule for the future, considering different plant designs given as investment strategies, using a mixed-integer linear programming (MILP) model in an uncertain environment is optimized. The different designs can be evaluated by calculating the net present value (NPV). Moreover, an analysis concerning current dynamics and uncertainties within spot market prices is executed. Furthermore, the influences concerning the variation of spot market prices compared to the influence of governmental subsidies, in particular, the flexibility premium, are revealed by computational results. In addition, the robustness of the determined solution is analyzed with respect to uncertainties.

Keywords Demand-oriented Biogas Plants, Gas Storage, Capacity Extension, Mixed-integer Linear Programming, Uncertain Electricity Market, Net Present Value

3.1 Introduction

Fossil resources are limited and will eventually run short. Therefore, a changeover in basic economic and ecological thinking is necessary. The renewable energy resources act, or EEG, is the central governmental element in Germany to accomplish this basic changeover in the energy sector. One objective of the German government is to increase the share of energy produced from renewable resources up to 45 % by 2025. To reach this objective, the shares of wind and solar sources will have to be increased. However, the energy generation provided by wind and solar energy is highly volatile. The energy demand is volatile as well. Thus, the issue within an energy system is to balance energy demand and supply. This has to be because of technical reasons. If the energy supply and demand within a grid is not balanced, the grid breaks down. Therefore, other flexibly schedulable energy sources are needed to compensate for the volatility. In relation to the EEG, these resources should not be fossil or nuclear but renewable. Biogas plants, operated flexibly, are a renewable resource that can be used to compensate this volatility with carbon-neutral generation and without using nuclear resources. The advantage of biogas plants is

[3] This paper has been written by Stephan Fichtner and Herbert Meyr (Department of Supply Chain Management, University of Hohenheim, Stuttgart). The paper has been published as one of the Hohenheim Discussion Papers in Business, Economics and Social Sciences. (Fichtner and Meyr, 2019)

that either the biomass can be stored to produce the biogas more demand oriented, or the produced biogas can be stored to produce the final product electricity demand oriented. The storage of biomass can be used to compensate for long-term volatility, and the storage of biogas is useful to compensate for short-term fluctuations. In contrast, it is more difficult to store electricity.

If the existing biogas plants are operated flexibly, there will be advantages not only for the energy grid operators, which are responsible for the energy distribution and the maintenance of the grid, the government or the private and commercial energy consumers, but also for the biogas plant operators. As mentioned, the flexible and demand oriented energy production in biogas plants can help to stabilize the power supply in the grid. Furthermore, power plants using fossil resources, which are currently used to compensate the volatility, can be substituted. The great advantage for the biogas plant operators is that they get the opportunity to generate additional revenues in high energy spot market price periods. Moreover, they will be independent of the EEG feed-in tariff, which is part of a governmental strategy to subsidize renewable energy resources. The feed-in tariff guarantees a fixed compensation for all of the produced energy within the first 20 years of plant operation.

As explained previously, biogas plants should be flexibly schedulable in the future to get a demand oriented power generation. Several possible adjustments concerning the biogas plants exist to reach this objective. Within this paper, a novel approach is developed to modify the technical biogas plant design in order to decouple the biogas and electricity production to increase flexibility. The generated power should afterward be sold through direct marketing at the power exchange EPEX Spot SE. The specific character of this modification is explained in Section 3.2.2. In brief, it is necessary to build a biogas storage capacity to decouple the biogas and electricity production. Thus, the storage is filled with biogas in times of low electricity prices and used to produce electricity in high price periods. To do so, in addition to the possibility to store biogas, it is necessary to have enough capacity to produce electricity out of the biogas. Hence, as another prerequisite, additional electrical capacity has to be installed. The size of the optimal biogas storage and additional electrical capacity depends on fluctuations in the energy market and thus on the potential to generate as many earnings as possible. A beneficial behavior for biogas plant operators is to produce and sell electricity in high price periods and store it in low price periods. In addition, governmental subsidies offer further incentives to invest in a flexibly schedulable plant. The decision about a specific adjustment of the biogas plant design is a long-term investment decision done by the biogas plant operator. In order to support this strategic, long-term investment decision to generate a robust solution for a risk-averse decision maker, decision support using optimization of an operational plant schedule for the future is given to evaluate the performance of the different plant designs. They can be evaluated by calculating the net present value (NPV) as a key figure using the arising cash flows and the initial investment.

In this work, a novel deterministic optimization approach is described. Therefore, at first, a basic model to optimize the operational plant schedule called OBPP (operational biogas plant problem) is developed. Secondly, this model is extended to support the investment decisions as mentioned (SBPP - strategic biogas plant problem). However, as the spot market prices are varying dynamically over time because of an uncertain behavior of energy demand and supply this variation is analyzed and considered using several scenarios. Therefore, significant sources of uncertainty are analyzed and determined. The examined investment planning problem is based on a real planning problem of a biogas plant operator in southern Germany. Nevertheless, the numerical experiments represent a fictional case, which is similar to the real biogas plant.

The remainder of this paper is organized as follows: In Section 3.2 an overview of the problem setting is given. Subsequently in Section 3.3 relevant literature is analyzed. Within Section 3.4 the deterministic optimization approach is described. Aforementioned, this model is tested using a fictional but close to reality case example in Section 3.5. Finally, Section 3.6 summarizes the results and identifies opportunities for extensions or general future research.

3.2 Problem setting

In Section 3.2 an overview of the problem setting is given. In particular, an overview of the energy demand in Germany in general, the functionality of biogas plants, the relevant market conditions and especially of the characteristics of direct marketing.

3.2.1 Energy demand in Germany

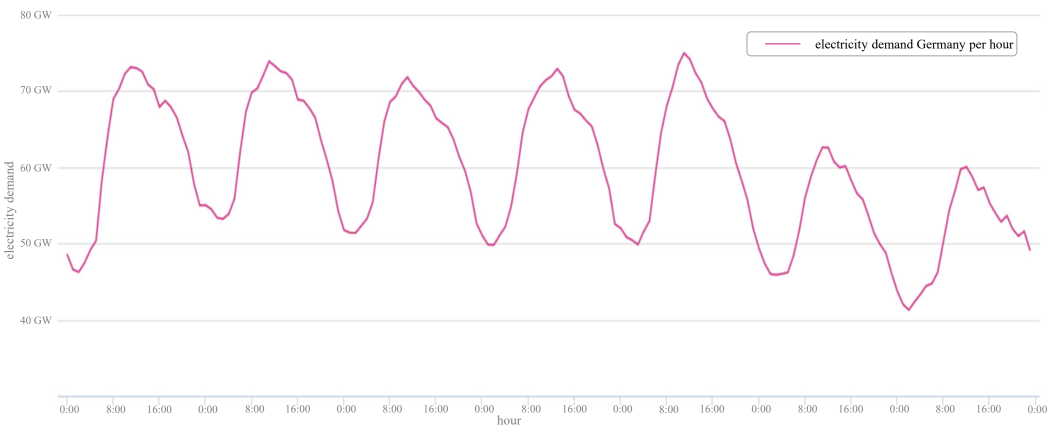

Figure 3.1: Electricity demand in Germany (Agora Energiewende, 2018)

As previously mentioned, the electricity production, as well as the electricity demand, are volatile. The behavior of the intraweek electricity demand in Germany, or in other words the load curve, is depicted in Figure 3.1. The figure is based on data for a typical week from Monday to Sunday in 2018. As demonstrated, the demand is characterized by an intraday and intraweek seasonal pattern. A demand peak during lunchtime on each day characterizes the first one. Additionally, there is a smaller peak or plateau during the afternoon. The intraweek pattern shows that the demand on weekdays from Monday to Friday is rather similar. Nevertheless, the patterns of Saturday and Sunday are very different. In addition to those two patterns, in general, another seasonal pattern can be observed regarding the electricity demand. Typically, the electricity demand in Germany is higher during the winter months than during the summer months. (BDEW Bundesverband der Energie- und Wasserwirtschaft e.V., 2018) To sum up, the electricity load curve in Germany is highly volatile and characterized by three seasonal patterns - intrayear, intraweek and intraday.

As declared, electricity production is volatile as well. The volatility is mostly based on the volatility of the renewable energy sources wind and solar. The production of those two energy sources is only partly controllable. Typical for solar energy is a production peak during lunchtime. Typical for wind power is that the production during the winter months is higher than during the summer months. However, both energy sources are highly volatile in a short-term planning horizon. (Fraunhofer ISE, 2018b)

The major issue within a national electricity power grid is that the electricity demand or consumption has in any time to be equal to the electricity production. Only if production and consumption are (nearly) equal, the power line frequency and the whole grid are stable. In Germany, the power line frequency has to be 50 Hz. There are mainly two technical possibilities to balance electricity production and consumption. Flexibly schedulable power plants are the first possibility. They can be conventional, like natural gas or coal power plants, or renewable, like pumped-storage power plants or biogas plants. The second possibility is import/export from/to neighboring countries. (Fraunhofer ISE, 2018a)

The organizational instrument to balance the electricity production and consumption is the energy exchange EPEX Spot SE. The energy demand and supply is traded in several markets at this energy exchange. Specific characteristics of the markets and the prices are described in Section 3.2.3. Nevertheless, in brief, the prices at the energy exchange are a result of specific energy demand and supply in a specific period. Depending on the ratio of demand and supply, the prices are high or low and thus volatile. This induces two main consequences. At first, it is necessary to balance electricity demand and supply to stabilize the power grid as explained. Further, the volatility of the prices offers the power plant operators the possibility to generate more earnings by producing and selling electricity in high price periods or in other words in periods, in which the electricity demand is high compared to the uncontrollable part of the electricity supply.

3.2.2 Biogas plant functionality

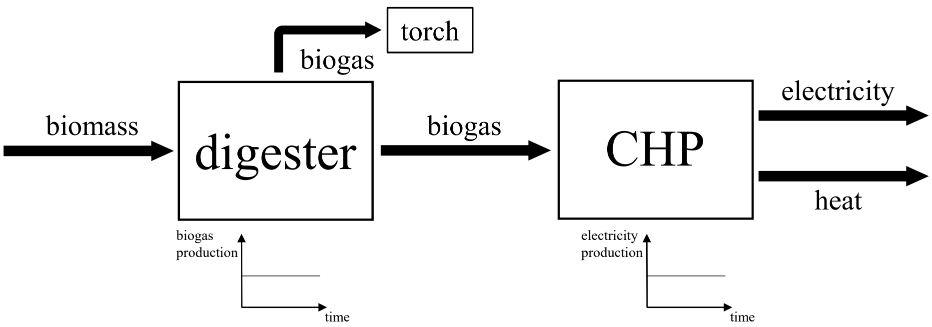

Figure 3.2: Conventional biogas plant configuration

Due to uncertain subsidies and changing governmental regulations, optimization strategies for biogas plants concerning flexible power generation and direct marketing become more and more important. Biogas plants provide the opportunity to generate carbon-neutral electricity out of biomass, or in other words renewable resources. There are several types of biogas plants running in the market. The majority of the plants uses the conventional way to produce energy. This conventional biogas plant design is depicted in Figure 3.2. Here, a digester is used to produce biogas out of substrate through combustion. As substrate, several types of biomass are possible. Common inputs are biowaste, wheat, rye silage, grass silage and maize silage. (Balussou et al., 2014),(BiomassV, 2016) Those types of biomass cannot only be used as inputs in biogas plants but also in other utilization pathways of the bioeconomy. Thus, there is a competitive situation on the market of biomass supply. (Fichtner and Meyr, 2017) As depicted in Figure 3.2 in the chart below the digester, the biogas is produced continuously within the digester. In other words, the biogas production rate over time is fixed. Afterward, the gas is directly burned in a combined heat and power (CHP) plant to produce electricity. During the combustion process, the by-product heat occurs. Within the CHP plants, several types of engines like gas-Otto engines or dual-fuel engines can be applied. The electricity production is continuous as well within this conventional configuration (represented by the electricity production chart below the CHP). The digester, as well as the CHP plant, are characterized by a specific capacity. As declared, the biogas is produced continuously within the digester. If there occurs a disturbance within the CHP plant(s) or if there is more biogas produced than can be combusted for other reasons, there is the possibility to burn biogas within a torch. Here, no electricity or other products are produced. Accordingly, no revenues are generated. This is just an opportunity to get rid of excess biogas. The main disadvantage of this biogas plant configuration is the inflexibility of the production rates of biogas and electricity. In order to produce the electricity demand oriented, the biogas plant design has to be adjusted. These adjustments cause investments. The resulting biogas plant configurations are explained in the upcoming paragraph. (Lehnert et al., 2011)

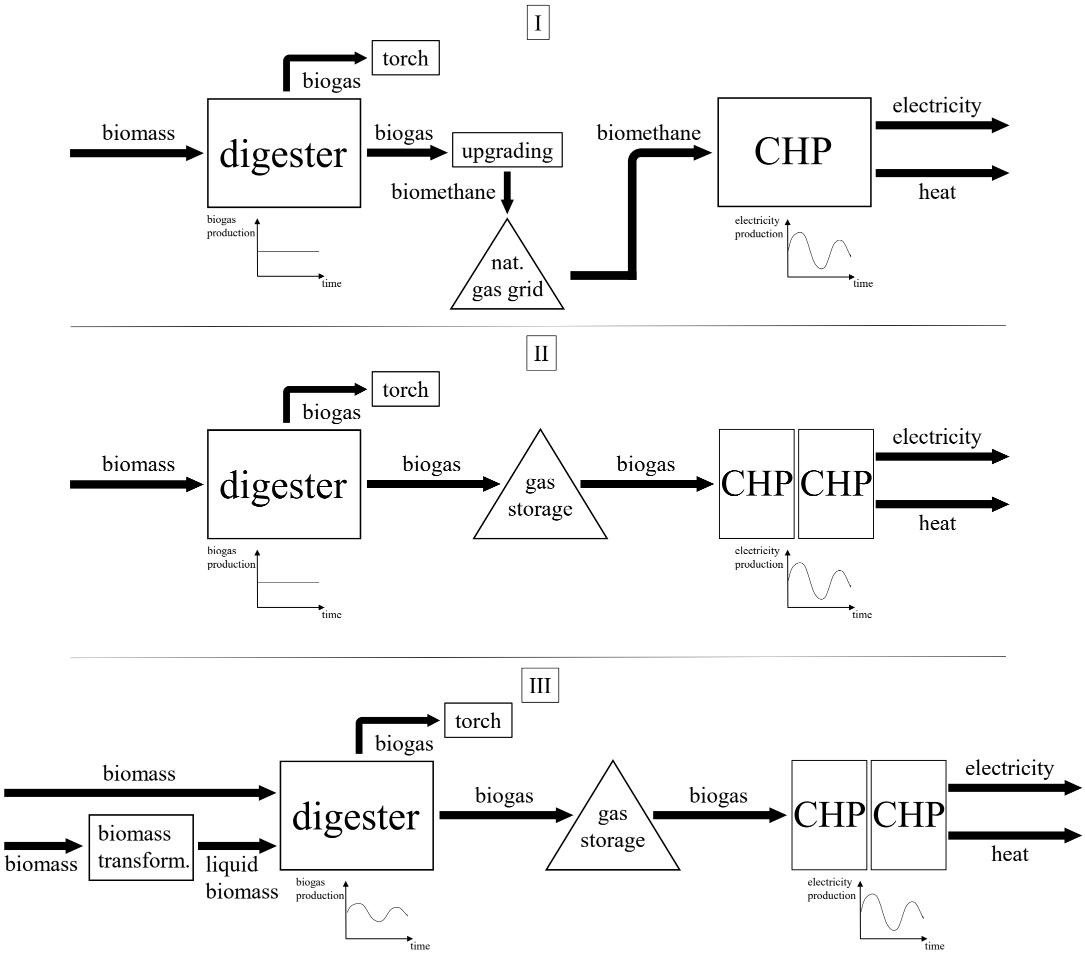

Figure 3.3: Further biogas plant configurations

Three types of flexible biogas plant configurations are distinguished. These configurations are shown in Figure 3.3. In the first configuration (type I) the produced biogas is transformed through an upgrade process in biomethane and afterward injected into the natural gas grid. The natural gas grid builds the infrastructure consisting out of pipelines and storages to supply natural gas to the consumers all over the country. If the biogas is upgraded and injected into the natural gas grid, the gas can be obtained from the grid and burned using CHP plants, but not necessarily at the biogas plant location, or can be used as biofuel. The biomethane can be purchased flexibly out of the natural gas grid. Thus, the electricity production (depicted in Figure 3.3 by the varying electricity production in the chart) is flexible as well and the biomethane can be burned demand oriented. The natural gas grid itself is used as a gas storage, which is not owned by the biogas plant operator. However, the infrastructure to transform the biogas into biomethane and a connection to the natural gas grid are necessary at the plant. The disadvantage of this approach is that the upgrading of the biogas is complex and expensive. (FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2013) The second configuration (type II) does not use an upgrading process. Here, a gas storage is included between the digester and the CHP plants. Hence, the gas- and electricity productions are decoupled. This means that the biogas production is still continuous but the electricity production is now flexible and thus decoupled. Besides, additional CHP capacity is necessary to increase the flexibility. This flexibility of the electricity production can be used to produce the electricity demand oriented. By doing so higher earnings can be achieved, if the production and sale of the electricity are made in high price periods. In times of low prices, no electricity is produced and the produced biogas is stored in the biogas storage. The flexibility potential of the plant depends on the size of the biogas storage and the CHP plant capacity. Biogas storages, as well as CHP plants, are available in different sizes and technologies. Important is that the size of the storage and the capacity of the CHP plant fit together. Because if, for instance, a lot of CHP plant capacity is installed but only a small biogas storage, there would not be enough available biogas to utilize the capacity of the CHP plants in most of the periods. The difference between type II and type III is that in the third configuration the biogas production within the digester is flexible as well. Therefore, for instance, the substrate has to be transferred into a liquid to influence the digestion process by variable substrate feeding. The advantage of all these three configurations in contrast to the basic configuration is that the electricity production is flexible and can for this reason be demand-oriented. This characteristic is necessary for beneficial direct marketing of electricity by generating additional earnings in the energy market. (Hahn et al., 2015),(Hahn et al., 2014b),(Hahn et al., 2014a),(Lehnert et al., 2011)

For all three configurations investments are necessary. In the following, only type II configurations will be examined. The reason is that the effort to reach the other two design configurations is much higher than to build a gas storage and include another CHP plant. For type I, a connection to the natural gas grid is necessary and the upgrading processes are very complex. For type III, the digestion processes in the digester and the biomass structure have to be adjusted. Additionally, another transformation process of solid biomass into liquid biomass can be necessary. Thus, the type II configuration is easiest to reach, as it is only necessary to build a gas storage and extend the CHP plant capacity. Nevertheless, investments are necessary to build the gas storage, install another CHP plant and adjust other infrastructure components. Additionally, the size of the storage and the maximum capacity of the new CHP plant have to be determined. As explained previously, the benefit of this biogas plant configuration is the possibility to generate more earnings by producing and selling electricity demand-oriented in high price periods. Hence, several investment strategies, consisting out of specific biogas storages and aligned CHP plant capacities, have to be assessed based on potential earnings in the energy market.

3.2.3 Market conditions in the German energy market

The market conditions in the German energy market determine the framework for the biogas plant operator's activities. In general, there are several possibilities for biogas plant operators in Germany to participate in the energy market. The possibilities are regulated in the EEG, which has changed a lot during the last years. The idea of the EEG in the year 2000 was to achieve a sustainable energy supply, decrease carbon emissions and develop energy technologies. (EEG, 2000) The first incentives for a demand oriented energy production were included with the amendment in 2012. Here, the two subsidies market premium and flexibility premium were introduced, which are incentives for a demand oriented energy production using direct marketing. (EEG, 2012) The functionality of those subsidies is explained in detail in Subsection 3.2.4.1. During the amendments in 2014 and 2017, the structure has changed again. Since 2017, the biogas plant operators have the opportunity to participate within a bidding model to sell their produced energy. (EEG, 2017) As the biogas plant operators have to act according to the EEG version of the time when the plant was put into operation, the following market participation possibilities, demonstrated as well in Figure 3.4, exist for operators of existing plants.

The first possibility is to take the EEG remuneration, or feed-in tariff, which is fixed for the first 20 years of plant operation and guarantees a fixed compensation per kWh of produced electricity, independent from the realized energy demand. The amount of the feed-in tariff is biogas plant specific because it depends on the used type of biomass, the maximum capacity of the plant and the used CHP technologies. The calculation is regulated in the EEG. (Bundestag, 2011) Here, the biogas plant would be run using the maximum capacity on each day - on full load operation.

Other market participation possibilities require a flexible operation of the biogas plant and are characterized as

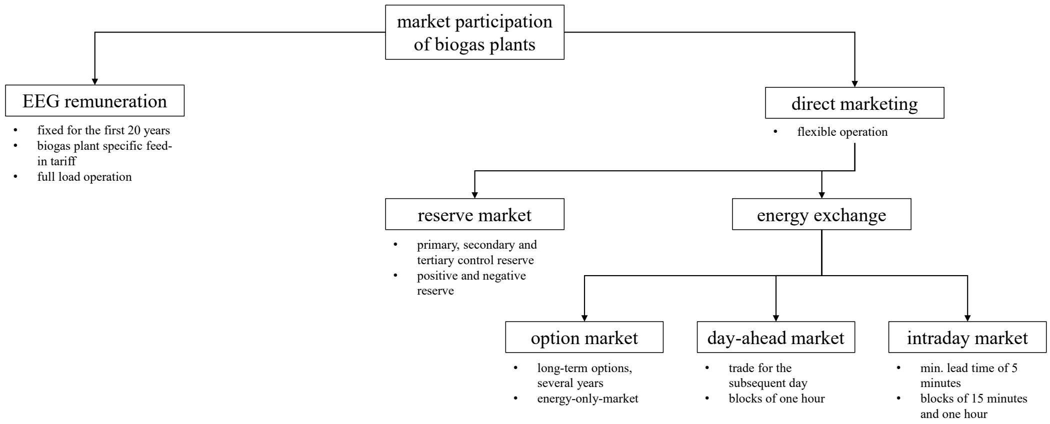

Figure 3.4: Market participation options of biogas plants

direct marketing options. If the biogas plant is operated flexibly, the first option would be to participate in one of the three reserve markets. Here, the primary, secondary and tertiary control reserve markets can be distinguished according to their planning horizon. As mentioned in Section 3.2.1, it is necessary to equalize electricity demand and supply to stabilize the power grid. The reserve markets are used to balance energy production and consumption. In all of the three markets, positive and negative reserve can be offered. Positive reserve means that in case of an unexpected high energy demand this demand is compensated by an increase in energy production. Negative reserve means that in case of an unexpected excess of energy supply the energy production of a plant is decreased. Both strategies are necessary to stabilize the electricity grid by balancing energy demand and supply. In the primary control reserve, the de- or increase of production has to be realized within seconds, within the secondary control reserve within five minutes and in the tertiary control reserve within 15 minutes. (Bundesnetzagentur. Beschlusskammer 6, 2011a),(Bundesnetzagentur. Beschlusskammer 6, 2011b),(Bundesnetzagentur. Beschlusskammer 6, 2011c)

The second option to participate in the market, if the biogas plant is operated flexibly, is to trade the energy production at the energy exchange EPEX Spot SE. Here, as well several markets exist. The first market is the option market. In this market, long-term options are traded with lead times up to six years. Additionally, this market is called an energy-only market, which means that only the amount of produced energy is compensated and not the reserved capacities as in the previously explained reserve market. The second market at the energy exchange is the day-ahead market. Here, the required energy of the subsequent day is traded in blocks of one hour. On this market, all tradings have to be finished until 12:00 CET of the previous day. This means that an electricity producer, e.g. a biogas plant operator, gives a bid for a specific amount of electricity in a specific hour on the next day for a specific market price on the power exchange. If this bid is accepted by the power exchange, the electricity producer is committed to fulfill his bid on the next day. If the bid is fulfilled, the electricity producer is compensated with the previously determined market price by the power exchange. If not, the electricity producer gets a financial punishment. The third market at the energy exchange is the intraday market. Here, energy in blocks of 15 minutes up to one hour is traded on a short term level. Apart from the shorter lead times, the functionality is similar to that of the day-ahead market. This market is used to minimize energy shortages and surpluses. The lead times can be decreased to five minutes. (Bundestag, 2011),(EEG, 2017) In the first 20 years of plant operation, the market premium and flexibility premium encourage the biogas plant operators to use direct marketing, reduce the maximum full load operation and thus produce their energy market-oriented and demand-driven. The market premium is a governmental subsidy, which warrants a payment for the plant operators with the amount of the difference between the biogas plant individual feed-in tariff an operator would get and the monthly average market price within the chosen market. Accordingly, there is the certainty for the biogas plant operator that on average at least the EEG feed-in tariff is achieved by choosing direct marketing. (EEG, 2017) The flexibility premium is an incentive for those biogas plant operators which run their plant demand oriented with a flexible schedule and is paid once in a year for the additionally reserved capacity for flexible energy production. Those plants can be used to reduce fluctuations in the power supply and thus to stabilize the voltage of the power grid. (EEG, 2014),(EEG, 2017) The functionality of the market and flexibility premiums is explained in detail in Subsection 3.2.4.1.

Operators of new plants or plants, which are older than 20 years, have to participate within another bidding model and have the opportunity to get a flexibility surcharge, which is similar to the flexibility premium. (EEG, 2017)

In the remainder, the optimization of biogas plants is based on the circumstances of direct marketing in the spot market, in particular, the day-ahead market. Here, the short-term flexibility potential of a flexibilized biogas plant can be used to generate more revenues than in the other markets. Moreover, most biogas plants are too small to participate in the reserve and option market.

On the spot market, the biogas plant operators have to interact with other market participants. Those participants are governmental institutions, other energy producers, transmission grid operators, the energy exchange as an institution, consumers and service providers. These service providers can help the biogas plant operators to place their produced energy on the market to generate as many revenues as possible. In many cases, several biogas plants are combined to so called virtual power plants (VPPs) by such a service provider. After the combination of the plants, the VPP is treated as a single plant and the total energy is sold together at the spot market.

3.2.4 Characteristics of direct marketing

Corresponding to the previous explanations, the following optimization approach is based on the market option direct marketing. Thus, the according requirements and subsidies are outlined in Section 3.2.4.1. The variability in the revenues and in particular the spot market prices is explained in Section 3.2.4.2.

3.2.4.1 Requirements and subsidies

As declared in the previous Section 3.2.3 the basic requirement for a biogas plant operator to participate in direct marketing is to run the biogas plant in a flexible design. Thus, the conventional biogas plant design, depicted in Figure 3.2, is not appropriate. Instead, one of the further mentioned and in Figure 3.3 shown designs is necessary.

Aforementioned, infrastructure investments are necessary to reach one of these flexible biogas plant configurations. Hence, there have to be incentives for the biogas plant operators to invest in their plant and produce the electricity demand oriented. One of these incentives is the possibility of generating more revenues in the spot market than taking the feed-in tariff. The revenues, an operator of a flexibly run biogas plant can generate, consist out of the spot market prices and governmental subsidies. Here, the two pertinent subsidies are the market premium and the flexibility premium as already mentioned in Section 3.2.3. As the prices in the spot market are a result of energy demand and supply, the prices are highly volatile. Accordingly, a beneficial behavior for biogas plant operators is to produce and sell electricity in high price periods.

In order to be entitled to receive the two subsidies, the biogas plant operators have to fulfill several requirements, which are regulated in the current version of the EEG. (EEG, 2017) Here, it is stated that the support through the governmental subsidies starts with the day the biogas plant is put into operation. The requirements for the market premium are as follows: The market premium is only paid for electricity, which is sold through direct marketing. If this is the case, the market premium is paid for a 20-year horizon. The biogas plant has to be flexible and remotely controlled. Thus, a perhaps charged direct marketing service provider is able to regulate the electricity production and feeding into the grid. Hence, the demand oriented electricity production is ensured. Additionally, the flexibility premium is characterized by the following requirements: The flexibility premium is a compensation for the availability of additional capacities within a plant to produce electricity demand oriented. As well as for the market premium, the biogas plant operator has an interest on the flexibility premium if the produced electricity is sold through direct marketing, or in other words, the biogas plant operator does not get the EEG feed-in tariff. Another requirement is that the already installed capacity has to be at least 20 % of the total installed capacity after a capacity extension. The biogas plant has to be run demand oriented according to the technical conditions. A surveyor has to certify that the biogas plant is able to produce electricity demand oriented. The certification in terms of the flexibility premium depends on individual decisions, because there could be more biogas plant specific requirements to fulfill. For this reason, there is still a remaining risk for the biogas plant operator to get approval or not. (EEG, 2017),(Bundestag, 2011)

The idea of the market premium is that it should be ensured that the biogas plant operator achieves at least on average the same payment per kWh through direct marketing as he would achieve through the biogas plant individual feed-in tariff. (EEG, 2017) Thus, the market premium is calculated as given in an example in Table 3.1.

Table 3.1: Example market premium

General calculation:	
Market premium =	
biogas plant specific feed-in tariff - average market price per month within the chosen market	
Example:	
Feed-in tariff:	11 ct/kWh
average market price per specific month:	5 ct/kWh
$\Rightarrow$ market premium in this specific month:	6 ct/kWh

The biogas plant specific market premium is the difference between the biogas plant specific feed-in tariff and the average market price within the chosen market. The average market price within the chosen market is calculated retroactively. Hence, the whole market premium is paid monthly retroactively. (EEG, 2017)

The market premium offers an incentive for the biogas plant operators to choose the way of direct marketing in general. Additionally, the flexibility premium offers another incentive to install additional electrical capacities within the plants to increase the potential of flexible production. Thus, the additionally installed flexible capacity is compensated with 130 EUR per kWh once in a year (130 EUR/kWhy).

The calculation of the flexibility premium is as follows: First, the flexible excess capacity per average hour in a year has to be calculated. Hence, the difference between the installed capacity in total and the already installed capacity, rated with a correction factor of 1.1 for biogas plants, which is defined by the German law, is calculated. The resulting flexible excess capacity for an average hour is compensated with 130 EUR/kWhy. The calculation and payment of the flexibility premium are made retrospectively. (EEG, 2017) For a fictional biogas plant example, the flexibility premium can be calculated as depicted in Table 3.2.

It is not allowed to use the additionally installed capacity continuously. The realized output of the current year has to be lower or equal than the previously realized output per year. If the requirements are met, the flexibility premium can be requested. If the flexibility premium is granted once, there is an entitlement in the premium within the upcoming nine years. Whether the requirements are met or not is verified after each year within this horizon. This important characteristic is expressed by two randomly chosen possible operational schedules within the previously given example and Figure 3.5. Within the example, the currently installed capacity was assumed as 500 kWh. Therefore, after an increase in electrical capacity, it is prohibited to produce on average more than 500 kW per hour on an average day. Both possible schedules demonstrate that on average exactly 500 kWh electricity is produced but the operational schedule can be very different. These two schedules are just examples of many possible ones. For instance, it is possible as well to produce less electricity than 500 kWh. (EEG, 2017)

Table 3.2: Example flexibility premium

currently installed CHP plant capacity (maximum amount of electricity per hour):	Cap = 500 kWh
additionally installed CHP plant capacity (maximum amount of electricity per hour):	Cap^{add} = 250 kWh
totally installed CHP plant capacity (maximum amount of electricity per hour):	Cap^{new} = 750 kWh
granted flexible excess capacity per hour:	$Flex^{min}$ = 250 kWh
maximum amount of electricity on average per hour in a year: $Prod^{max} = Cap^{new}$ - $Flex^{min}$ = 750 - 250 = 500	
granted (*minimum*) flexibility premium per year: $(Cap^{new} - Prod^{max} \cdot 1.1) \cdot 130$ = $(750 - 500 \cdot 1.1) \cdot 130$ = 26,000 EUR	
one possible operational plant schedule (solid in Figure 3.5): 12 hours maximum amount of electricity per hour 750 kWh; 12 hours maximum amount of electricity per hour 250 kWh	
second possible operational plant schedule (dashed in Figure 3.5): 8 hours maximum amount of electricity per hour 0 kWh; 16 hours maximum amount of electricity per hour 750 kWh	

3.2.4.2 Fluctuation of revenues

As described, the participation within direct marketing is characterized by volatilities of prices and revenues. In order to assess the profitability of an energy marketing strategy, it is necessary to analyze the fluctuation within the possible revenues. As the prices at the spot market are a result of specific energy demand and supply, the prices are fluctuating significantly. This fluctuation could even mean that the spot market prices, in contrast to the energy demand, are negative, which means that the power plant operator has to pay for his power supply. One reason for the fluctuation is the energy supply from the renewable sources wind and solar. For example, during the middle of the day, when the energy supply from solar systems is typically high, the spot market prices are lower than in the hours before and after. The fluctuation of the spot market prices is depicted in the boxplot in Figure 3.6. Here, boxplots for every single month of a year and a boxplot for all data of the spot market prices from the day-ahead market in 2011 to 2015 are depicted. It is possible to interpret these boxplots to get an idea of the price data characteristics like measures of location, the dispersion, the interquartile range or the existence of outliers. As demonstrated, the prices are distributed between -22.1 and 21 $Cent/kWh$. Additionally, it is displayed that many price realizations are outside of the blue boxes, which represent the prices between the first and third quantile. This characteristic presents the variance within the price data. However, the boxplots also show that this variance differs between the individual months. The objective of a flexible plant schedule combined with direct marketing is to produce and sell energy when the spot market price is as high as possible and to store the biogas in times of low prices. In the following, several sources of uncertainties are discussed. Thus, strategic, long-term developments and repetitive, or in other words seasonal, dynamics are distinguished.

Strategic development - Market price development:

The first analyzed source is the strategic, long-term development of the spot market prices at the day-ahead market from 2011 to 2015. The development is demonstrated in Table 3.3. As depicted in the table, the yearly mean of the spot market prices is decreasing through the years. This trend is remarkable because the development of customer electricity prices is totally reverse. The customer prices were rising steadily through these years. (Statistisches Bundesamt, 2017) It is not obvious to give reasons for this decreasing process. One reason might be the decreasing price for crude oil during these years, but there are certainly other influencing factors. For reasons

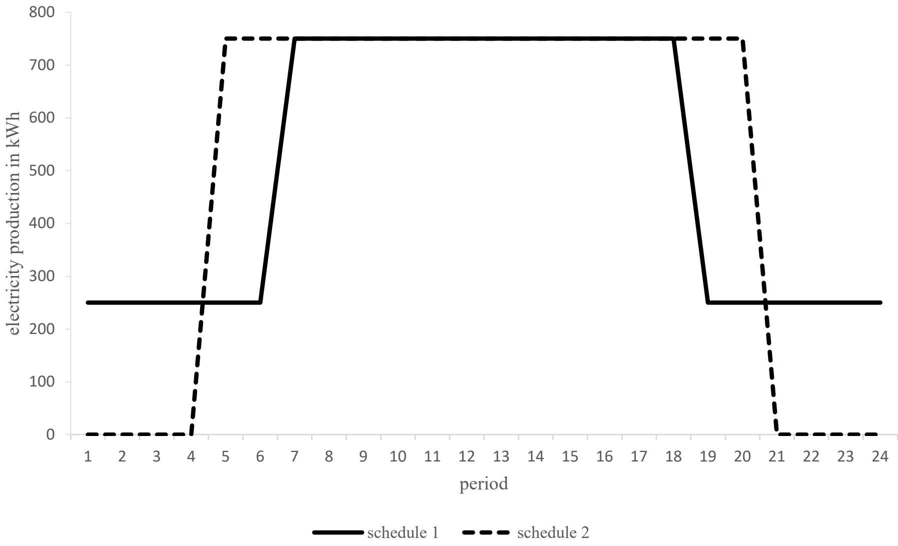

Figure 3.5: Two possible operational schedules concerning the flexibility premium

of abstraction, these influencing factors are not analyzed in detail. Most important is to forecast whether this decreasing process will go on in the future or not. Within a study from Schlesinger et al. (Schlesinger et al., 2014) the various influencing factors are analyzed. One of the conclusions of this study is that the decreasing of the spot market prices will go on until 2020. From this year on the prices will start increasing. However, it is still uncertain whether this forecast will be correct or not. Hence, this uncertainty should be covered within strategic planning tasks in biogas plants.

Table 3.3: Long-term development of day-ahead spot market prices from 2011-2015 (EPEX Spot, 2018)

year	mean [Cent/KWh]
2011	5.11
2012	4.26
2013	3.78
2014	3.28
2015	3.16
average 2011-2015	3.92

Strategic development - Governmental subsidies:

As described in Section 3.2.3 and 3.2.4.1, the achievable revenues for a biogas plant operator using direct marketing consist of the spot market prices and governmental subsidies. Since the revenues at the spot market have been rather low in comparison to, for example, the market premium, it is necessary to evaluate the uncertainty of these revenues as well. The amount of the two subsidies market premium and flexibility premium is declared in the EEG. In the past 17 years since the first version of the EEG, six amendments of the law have been published. This means that on average one EEG version is updated after not even three years. The planning horizon of strategic planning problems is usually several years. Accordingly, the time between two EEG amendments is probably shorter than the considered planning horizon. Nevertheless, the impact of new regulations on existing plants is rather low because existing plants are regulated using the EEG version, which was the current version at the point

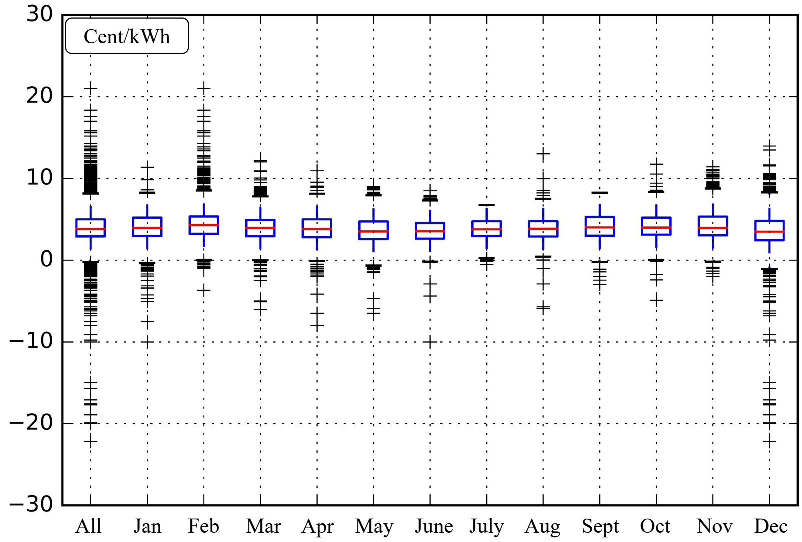

Figure 3.6: Boxplot of day-ahead spot market prices from 2011-2015 (EPEX Spot, 2018)

in time when the plant was built resp. went on stream.

As declared by law, similar to the feed-in tariff, the market premium is fixed for the first 20 years of plant operation. After these years, the operator of a biogas plant has no entitlement on this subsidy. (EEG, 2017) The flexibility premium is fixed, as well. However, only for ten years after application and the first flexible power generation. As a result, the governmental subsidies are rather certain, if they are granted once. (EEG, 2017) Nevertheless, the circumstances for (flexible) biogas plants can change in the future because of changes in the appropriate laws. For this reason, the decision maker has to decide if it is better to make the investment now or later because in the future the subsidies could be higher or lower if the investment is made then. Additionally, there is the risk for the biogas plant operator that the requirements are not fulfilled and especially the flexibility premium is not granted by the surveyor.

Dynamics and seasonalities:

As explained previously, uncertainties and repetitive dynamics should be strictly distinguished. As given in Figure 3.6, there is a seasonal intrayear price fluctuation or dynamic. The average of the prices is noticeably lower in summer than in autumn or winter. Furthermore, the variance differs between specific months. For example in December, the variance is very high compared to for example in July or other months. Moreover, in December an untypically high occurrence of negative outliers exist. One reason for these outliers is that in December there are a lot of holidays and those days have an unusual price pattern which leads to a higher variance within the whole month. In February, the data is characterized by a great number of positive outliers. These characteristics mean that the measures of location and the dispersion but also the skewness differs between the specific months.

The seasonality during the months of a year is demonstrated in Figure 3.7 as well. Within the figure, the average of the spot market prices of the day-ahead market from 2011 to 2015 for each month and each time during the day is shown. Low spot market prices are represented by red colors and high prices are represented by green colors. As depicted, the prices during fall, winter and early spring (Sept. - Feb.) are on average, especially by day, higher than during the summer months. Additionally, another seasonality is depicted - an intraday seasonality. Here, the prices are lower during the night, characterized by an increase in the morning, a decrease during lunchtime and another increase during the early evening again. However, the amount of volatility is different within the specific seasons of a year.

The mentioned short-term seasonal price pattern during one day is revealed in Figure 3.8 as well. The figure shows the mean of the above described price data, specific for each day and each hour of the day. As given, the fluctuation from Monday to Friday is rather similar compared to the fluctuation on Saturday and Sunday, which is more different. From Monday to Friday, there are typically two price peaks, one during the morning and one in the early evening. These peaks can be used to generate high earnings, if a lot of electricity is produced and sold during that time. The two price peaks are caused by the energy demand and the feed-in of electricity produced out of solar power. The energy demand is typically higher during the day than during the night. Thus, the prices during the day should be higher than during the night. However, as the feed-in of solar-based electricity has its peak typically during lunchtime, the energy prices decrease during this part of the day because the energy supply is very high. On the weekend, these peaks are not only lower but also later during the day. On Sunday, the afternoon peak is significantly higher than the peak at lunchtime.

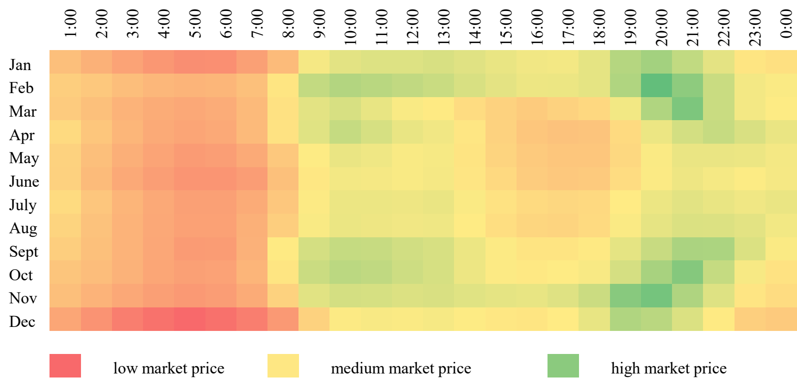

Figure 3.7: Heatmap of spot market prices per month and hour (EPEX Spot, 2018)

Finally, it can be summarized that the prices at the day-ahead market are characterized by three different seasonal patterns or dynamics. An intrayear, intraweek and intraday pattern. This characteristic should be covered within strategic planning problems in biogas plants to get an appropriate approximation of possible future earnings.

3.3 Literature

The objective of this work is to solve the planning problem of a real biogas plant in southern Germany as described previously. Biogas plants operated flexibly should be used to compensate differences of energy demand and supply within the power grid to stabilize it. By doing so, the biogas plant operator has the possibility to generate more earnings by producing and selling electricity in times of high price periods. In order to achieve a flexibly schedulable biogas plant, the plant design has to be adjusted to decouple the biogas and electricity production. The starting situation within the real biogas plant is the design of a conventional biogas plant. The design is adjusted to reach a type II configuration. Therefore, a biogas storage and additional electrical capacities are necessary. The investment decision concerning the size of the biogas storage and the additional electrical capacity depends on the fluctuation of the energy market prices and thus the opportunity to generate as high earnings as possible. To asses several investment strategies, consisting out of several possibilities for biogas storages and additional CHP plants, an operational plant schedule based on uncertain energy market prices is optimized. The optimization of the operational schedule with an extraordinary high granularity - on an hourly basis - is necessary, because of the identified sources of uncertainty. An optimization and not only a simulation of the operational schedule is needed, because the scheduling includes revenue-effective decisions, which are crucial for the strategic investment decision. Hence, in the following literature about design and operational plant schedule optimization in biogas plants and related

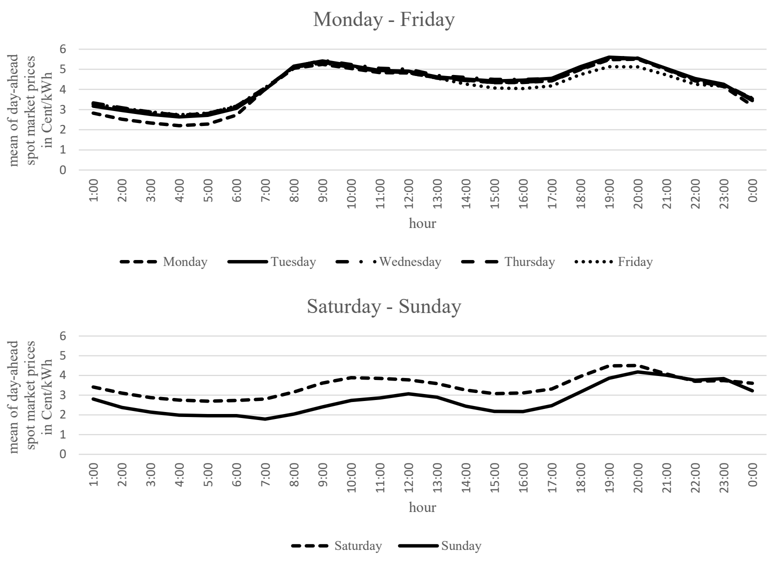

Figure 3.8: Mean of spot market prices per day and hour (EPEX Spot, 2018)

energy sources based on direct marketing and spot market prices is reviewed to ascertain whether appropriate approaches already exist to solve the real case problem as mentioned. The related literature is clustered into six groups. Literature concerning the optimization of biogas plants (BGP), combined heat and power plants (CHP), virtual power plants (VPP) and hydro power plants (Hydro). Additionally, literature about price forecasting (Price) and other literature concerning investment decisions under uncertainty in the general electricity market (Invest.) is distinguished.

In order to define the important field of research in more detail, the Supply Chain Planning Matrix (SCP-Matrix) is used to classify the different planning problems of a biogas plant operator. The adjusted SCP-Matrix for a biogas plant operator is depicted in Figure 3.9. Here, the different planning problems are covered using typical planning modules of Advanced Planning Systems. (Meyr et al., 2015) From a biogas plant operator's point of view, several planning tasks of the original SCP-Matrix can be neglected. Those planning tasks are colored in grey. Typically, distribution tasks, as well as demand fulfillment tasks, do not play any role for biogas plant operators because they feed in the produced electricity directly to the grid and have typically only one customer. Additionally, as substrate, several types of biomass are possible, which are assumed as available at the plant. Accordingly, purchasing and Material Requirements Planning tasks play a minor role for biogas plant operators. Moreover, the strategic planning problem of adjusting the biogas plant design is solved by optimizing an operational schedule. Hence, mid-term Master Planning tasks are not part of the problem. The planning problems of the current work can be categorized into the long-term Strategic Network Planning (SNP), the mid-/short-term Demand Planning (DP) and the short-term Production Planning and Scheduling (PPS). The biogas plant design as a long-term decision (SNP) is optimized on basis of an idea of uncertain revenues based on uncertain spot market prices (DP) using an optimization of an operational biogas plant schedule (PPS). Distinctive for the current DP-problem is that the specific energy demand determines the market price in combination with the energy supply. Nevertheless, as the total demand in an economy is much greater than the production capacity of one single biogas plant, the energy demand for one plant can be assumed as infinite. Therefore, the prediction of the uncertain spot market prices is the crucial problem.

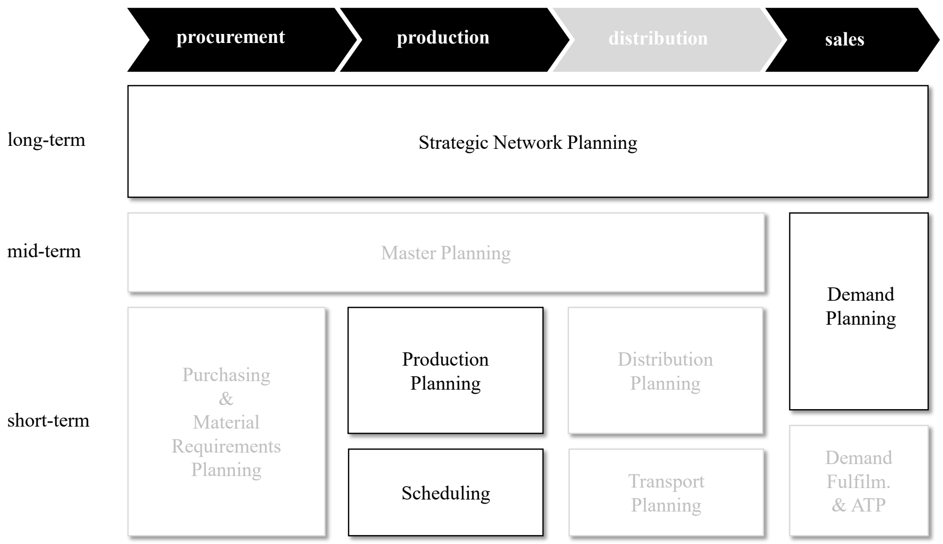

Figure 3.9: SCP-Matrix for a biogas plant operator using planning modules (see Meyr et al. (2015))

3.3.1 Related publications

As a first group of literature, existing literature about biogas plant optimization using direct marketing is reviewed. Gohsen and Allelein (2015) have published an approach to optimize the electricity production out of biogas based on a volatile demand. Within their approach, they consider storage capacities but the biogas plant design is given and not changed. They compare different cases of marketing. The first case is taking the feed-in tariff, the second one considers direct marketing and in the third one direct marketing and the flexibility premium are considered. No information about the specific optimization model is included in the publication. Heffels et al. (2012) introduced several business models for direct marketing of electricity from biogas plants using operations research models. They distinguish between biogas and biomethane plants, whereas their definition of biomethane plants is as follows: The produced biogas out of the digester is upgraded and injected into the natural gas grid. Afterward, the gas is used in CHP plants to produce electricity. Moreover, they distinguish between a fixed or demand driven production of electricity. The spot market prices within their model are given as deterministic parameters and since only the operational plant schedule is optimized, no investment decision is made. Besides, as the publication is from 2012, the demonstrated approaches are based on outdated governmental regulations. Additionally, Hochloff and Braun (2014) published a model to optimize the operational biogas plant schedule regarding excess power units and storage capacities. They use the principle of rolling planning to improve their results and distinguish between several energy markets but take the spot market prices as deterministic parameters. Additionally, the results of the generated schedules are compared for a few plant designs. However, the biogas plant design itself is not optimized.

Only one investigated publication deals with the operational optimization of CHP plants. This work is published by Beraldi et al. (2008) and shows an approach for the integrated optimization of production and trading of thermoelectric units or in other words CHP plants. Within this approach, the uncertainty on the day-ahead market is considered in a price taker model. In order to handle the stochasticity in the model, several scenarios are distinguished.

As a third group, publications concerning direct marketing of hydro-power plants are analyzed. Within this review, four representative publications are considered. Additionally, more general information about hydro-power plant optimization can be found in Singh and Singal (2017). The first publication about short term hydro-power scheduling is from Belsnes et al. (2016). Within this work, a stochastic and a deterministic approach are compared on the basis of uncertain electricity prices. The stochastic approach is modeled as a successive linear program. The optimization approach is based on the Norwegian market and thus the legal framework there. Price scenarios, generated using a simulation of stochastic processes to show combinations of fundamental influencing factors, are used as inputs with the same probability. In another publication by Chazarra et al. (2016) the optimal hourly schedule within a weekly scheduling process is examined. They use price scenarios for each hour of a week based on the Spanish market in a price taker model to optimize the operational plant schedule. Fleten and Kristoffersen (2008) deal with the commitments between energy producers and other market participants based on the chosen market regarding an optimization of the short-term planning of a hydro-power plant. They use a stochastic model formulation and scenarios based on time series models to derive a solution for the Norwegian day-ahead market. Another model about short-term hydro-power scheduling is published by García-González et al. (2007). They use a stochastic optimization model with price scenarios. Within this approach, the market prices are exogenous variables and modeled via scenarios. Furthermore, they consider the risk aversion of a decision maker in their approach using the Conditional Value at Risk (CVaR).

In a fourth group of literature, publications concerning investment decisions under uncertainty in the general electricity market are reviewed. Blyth et al. (2007) developed an approach to make investment decisions under risk. Within this approach, regulatory uncertainties concerning for example subsidies are modeled. Even though, no details about the specific modeling are given within the publication. The authors explain a dynamic programming approach to include the risk management of plant operators of coal and gas fired plants or carbon capture and storage (CCS) technology plants. Dynamic programming is used as well by Kumbaroğlu et al. (2008) to evaluate year-by-year investment decisions for energy producers. Here, the price uncertainty is considered using stochastic processes. Additionally, it is assumed that the demand is price sensitive. The optimization approach is based on the legal framework of the Turkish energy market. A real options approach (ROA) is used by Yang et al. (2008) to assess investment alternatives in the energy sector. Governmental regulations are assumed as uncertain within this approach. The objective of the work is to quantify the costs of uncertainty. The ROA is part of a dynamic programming approach to derive a solution for the investment decision. As energy sources gas, coal and nuclear power plants are considered. As the publication is from 2008, the approach is based on outdated legal regulations.

In a further group of literature, publications with a focus on uncertain electricity prices are analyzed. Similar to the group hydro-power planning, only a few representative and typical approaches are explained here. Additionally, more general information about dealing with uncertain electricity prices can be found in Haghi and Tafreshi (2007) and Möst and Keles (2010). Keles et al. (2012) compare and evaluate several models to forecast electricity spot market prices. Within these models, it is possible to include the stochastic behavior of the prices as well as negative prices and price jumps. The forecasted prices are not used as inputs for further calculations or optimizations. In another publication of Keles et al. (2016) the forecasted electricity prices of the day-ahead market are used as inputs for the energy trading. The authors explain that the influencing factors on the prices can be clustered, but as the clustering of these factors has a fundamental influence on the quality of the forecasts, it is still difficult to derive a robust forecast. In order to derive a forecast, artificial neural networks are used. Weron (2006) is dealing with the modeling and forecasting of electricity loads and prices. He describes the legal frameworks in several energy markets, analyzes the characteristics of the time series of loads and prices and compares several forecasting methods. No application of the forecasts is considered. Ziel and Steinert (2016) published a new approach to forecast electricity prices. Within their approach, not the price itself is forecasted but its source - the relationship of the sales and purchase curves. By using the sales and purchase curves the non-linear behavior of the prices, as well as other characteristics of the time series and bidding structures can be modeled. The approach is based on the EPEX market. In an earlier publication Ziel et al. (2015) revealed an econometric model to forecast hourly prices on the EPEX market. In order to derive this forecast, they combine several established methods. Furthermore, changes in the market due to a change in the energy mix are considered. The derived forecasts are not used for further applications.

In a last group of literature, publications considering direct marketing and flexible scheduling in VPPs are analyzed. Similar to the group hydro-power planning, only a few representative and typical approaches are described here. Additionally, more general information about the operational optimization of VPPs can be found in Nosratabadi et al. (2017). A stochastic mixed integer linear programming model for the operational scheduling of VPPs in the Chinese market was published by Ju et al. (2016). The authors consider the robustness of the solution in their published stochastic model and assume a VPP consisting of solar, gas turbine and energy storage systems. To generate a short-term plan, based on the day-ahead market, the uncertain revenues are simulated. The publication of Nojavan and Zare (2013) deals with the optimal bidding strategy of an operator of a VPP in a price taker model. The bidding strategy of the day-ahead market is analyzed. Hence, a short-term planning horizon is regarded. Within the approach, the uncertainty in the prices is considered and risk-averse resp. risk-neutral decision makers are compared. Furthermore, the robustness is considered using a robustness function. Pandžić et al. (2013) are using a stochastic optimization model to build an optimal operational schedule of a VPP consisting of intermittent sources like wind or solar and flexible resources like storages. The approach is based on the EPEX day-ahead and balancing market. Peik-Herfeh et al. (2013) distinguish in their work between several bidding strategies in the day-ahead market by considering uncertain spot market prices. The assumed VPP consists of dispatchable and stochastic units. Within this approach, no market specific subsidies are considered. A two-stage stochastic model is used by Tajeddini et al. (2014) to optimize the short-term operational schedule of a VPP. Within this approach, an expected value model with scenarios is used to derive a solution for a risk averse decision maker. The CVaR is used as a risk measure. The assumed VPP, which produces electricity for the day-ahead market, consists out of a diesel generator, a micro turbine and a battery bank. As a last related publication, the work of Zamani et al. (2016) is reviewed. Within this work, the operational schedule of a large scale VPP is optimized using a stochastic modeling approach. In order to derive a scenario-based decision, scenarios for various stochastic influences are built. Uncertainty in the day-ahead prices, the electrical demand and the power generation are considered. Within the VPP, consisting out of solar, CHP, wind turbine and storage systems, electrical and thermal resources are distinguished.

3.3.2 Classification scheme and discussion

Table 3.4 further classifies and summarizes the models described previously. The following attributes and acronyms are used to analyze the related literature in greater detail.

Cluster: The related literature is firstly grouped into the previously explained clusters. Here, publications dealing with biogas plants (BGP), CHP plants (CHP), hydro-power plants (Hydro), investment decisions under uncertainty in the electricity market in general (Invest.), uncertain electricity prices (Price) and virtual power plants (VPP) are distinguished.

Model: Furthermore, the publications are analyzed concerning modeling characteristics. Here, static optimization models (SO.), simulation models (S.), dynamic programming models (DyP) and forecast models (fc.) are distinguished.

Supply Chain Planning (SCP): Additionally, the literature is analyzed in relation to the previously introduced planning tasks of the SCP-Matrix. Thus, the publications are assessed regarding the previously declared three important planning tasks represented by the naming of typical planning modules - Strategic Network Planning (SNP), Demand Planning (DP) and Production Planning and Scheduling (PPS).

Uncertainty: As the uncertainty in spot market prices is a crucial part of problems in the energy market, the consideration of uncertainty within the published models is analyzed as well. Here, deterministic model formulations (det.) and stochastic models (sto.) are distinguished.

Characteristic (charact.): Two more modeling characteristics are analyzed using a further step. Here, it is analyzed if the authors deal with the robustness of their solution (rob.) and which type of risk attitude is considered. Those publications, which consider a risk averse decision maker (risk av.) are marked.

Table 3.4: Related literature

		model				SCP			uncertainty		charact.	
	Cluster	SO.	S.	DyP	fc.	SNP	PPS	DP	det.	sto.	rob.	risk av.
Gohsen and Allelein (2015)	BGP	x					x		x			
Heffels et al. (2012)	BGP	x					x		x			
Hochloff and Braun (2014)	BGP	x					x		x			
Beraldi et al. (2008)	CHP	x	x				x	x		x		x
Belsnes et al. (2016)	Hydro	x					x	x	x	x		
Chazarra et al. (2016)	Hydro	x					x	x	x			
Fleten and Kristoffersen (2008)	Hydro	x					x	x		x		
García-González et al. (2007)	Hydro	x					x	x				x
Blyth et al. (2007)	Invest.			x		x						x
Kumbaroğlu et al. (2008)	Invest.			x		x		x		x		x
Yang et al. (2008)	Invest.			x		x						x
Keles et al. (2012)	Price		x		x			x				
Keles et al. (2016)	Price				x			x				
Weron (2006)	Price				x			x				
Ziel and Steinert (2016)	Price		x		x			x				
Ziel et al. (2015)	Price				x			x				
Ju et al. (2016)	VPP	x					x	x		x	x	
Nojavan and Zare (2013)	VPP	x					x	x		x	x	x
Pandžić et al. (2013)	VPP	x					x	x		x		
Peik-Herfeh et al. (2013)	VPP	x					x	x		x		
Tajeddini et al. (2014)	VPP	x					x	x		x		x
Zamani et al. (2016)	VPP	x					x	x		x		
New optimization approach	BGP	x				x	x	x	x	x	x	x

The analysis of the literature leads to the following conclusions:

BGP: Three models for the optimization of biogas plants can be identified. Not one of these models considers an investment decision. Furthermore, the spot market prices are given as exogenous variables and deterministic optimization approaches are used. To the best of our knowledge, there does not exist any publication taking investment decisions and uncertainty into account. Moreover, some of the analyzed publications are based on outdated versions of the EEG. Nevertheless, the authors are dealing with the optimization of an operational biogas plant schedule. Thus, these deterministic models can be used as a part of an optimization approach with the objective to optimize an operational schedule, which is dealing with uncertainty.

CHP: The presented model does not include an investment decision. Indeed, a stochastic model formulation and the risk attitude of the decision maker is considered, but the plant characteristics of a general CHP plant cannot be used for biogas plants without adjustments, although those two energy sources are rather similar. The reason is that a CHP plant, in general, has a one-stage production process. Here combustible material, renewable or conventional, is burned to produce electricity. As demonstrated in Section 3.2.2 a biogas plant is characterized by a multi-stage production process, in which in a first stage biogas is produced out of substrate. In a second stage, electricity is produced out of biogas using a CHP plant. Hence, the whole system of a biogas plant is much more complex than that of a separate CHP plant. Nonetheless, the results and conclusions of this publication can be helpful to optimize the electricity generation process within a biogas plant.

Hydro: As in the publications of the previously analyzed clusters, not one model for hydro-power plants considers an investment decision. Partly, stochastic formulations are used but the models are based on energy markets in other countries than Germany, hence, on other legal frameworks. Moreover, similar to the models considering

CHP plants or VPPs, the plant characteristics are related, as the plants can be run flexibly using preproducts (water, biogas) out of storage. However, the conditions and therefore the restrictions of storing water in a reservoir are different compared to a biogas storage. Apart from the differences in the specific plant characteristics and restrictions regarding the storage, other parts of the published models can be helpful to model and optimize an operational schedule in a biogas plant. The specific modeling of the prices can be used in a similar way for optimizing a biogas plant schedule because in all of the models a plant schedule for hydro power plants, depending on volatile spot market prices, is generated.

Invest.: The three identified models concerning investment decisions in the energy sector are different in contrast to all other considered models. They include an investment decision into the model. However, as they are energy source independent, they do not include a short-term production planning. Moreover, they use dynamic programming and in some of these publications no information about the specific model formulation is given. Furthermore, some of the models are based on outdated legal frameworks. Nevertheless, in contrast to all other considered models, an investment decision is made. For this reason, these ideas of modeling an investment decision in general together with the conclusions for optimizing the operational schedule from other models can be helpful to combine both decisions in one model for a biogas plant design optimization.

Price: The models considered in the cluster "Price" have the advantage that a real demand planning or in particular a price forecast is implemented. Nevertheless, as these forecasts are not used as inputs for further calculations, the models represent only a small part of the optimization problem within a biogas plant. Nevertheless, the conclusions of these publications can be used within an integrated biogas plant optimization approach for instance to produce price forecasts or price scenarios. The role of these forecasts within the later on developed optimization approach is specified in Section 3.4.1.

VPP: The identified models concerning VPPs do not consider investment decisions. However, all analyzed models use a stochastic model formulation and some of them consider the robustness of the generated solution and the risk attitude of the decision maker as risk averse. Hence, parts of these approaches, especially the modeling of the robustness of a solution and the risk attitude of the decision maker, can be used together with relevant parts from the previously described publications as inputs for biogas plant optimization problems, if the plant characteristics would be adjusted.

To sum up, what is missing in the literature is an approach for the optimization of the design of a biogas plant considering direct marketing and thus uncertain revenues by optimizing an operational plant schedule. Additionally missing is the consideration of the robustness of the generated solution and the assumption of a risk averse decision maker. Risk aversion is a typical risk attitude of biogas plant operators, which are often small farmers. An approach, which is able to do this, is developed in Section 3.4. Therefore, parts of the previously described publications can be used to model separate subproblems.

3.4 Solution approach

Within Section 3.4 the solution approach to the identified strategic planning problem is introduced. Here, at first an overview of the approach is given in Section 3.4.1. Afterward, the assumptions of the developed models are explained in Section 3.4.2. Subsequently, optimization models for the operational (operational biogas plant problem - OBPP, Section 3.4.3) and strategic planning (strategic biogas plant problem - SBPP, Section 3.4.4) are presented.

3.4.1 Overview of the solution approach

As mentioned in the previous section, missing in the literature is an approach for design optimization in a biogas plant considering direct marketing and thus uncertain revenues by optimizing an operational plant schedule. In order to support the investment decision of adjusting the design of a conventional biogas plant into a flexible type II plant considering uncertain revenues, a multi-stage approach is developed. The specific parts of this approach, which is embedded in the legal framework in Germany and considers uncertain influences of the energy market, are illustrated in Figure 3.10. As depicted, the heart of the approach is a deterministic mixed-integer linear planning (MILP) model for the investment decision called SBPP.

However, before the model is applied, price scenarios for different spot market price forecasts are generated. Therefore, the influencing factors on the spot market prices are analyzed in a first step. Subsequently, the factors with a significant influence are identified. Using these influencing factors and time series decomposition, an expected price development for the future can be generated. However, this expected price is characterized by a forecast error. In order to consider the uncertainty within the expected price, several scenarios are generated. (Section 3.5.3.1) The idea is to model the risk of not reaching the expected price in a negative way or exceeding this price, by building the best and worst case as extremes and the expected price as an average case. Besides, further scenarios between these extremes are possible. Additionally, further scenarios are generated concerning significant legal conditions, namely the EEG regulations. Here, similar to the price scenarios, extreme scenarios for the development of the legal framework are built. (Section 3.5.3.2) One scenario, which is used in the determined SBPP model consists of one combination of one price scenario and one EEG scenario. As each scenario for the spot market price and the EEG conditions represents a realization of the appropriate random variables, these scenarios can be used as deterministic input data within the optimization model.

In addition to these scenarios, deterministic input data concerning the plant characteristics is necessary. Here, a finite number of investment alternatives ($j = 1,...,J$), representing additional biogas storage and CHP plant capacities, is assumed. (Section 3.5.2)

As (Fleischmann et al., 2015) have shown, a strategic design planning problem like an investment decision integrates two planning levels, which are the strategic structural decisions and the mid-term operational ones. In order to optimize the design of a biogas plant, the structural decisions concerning investments are modeled in the SBPP model, while the operational material and financial flows are modeled in the OBPP model. In general, the decisions on the strategic level determine the framework for the operational planning. Additionally, the resulting operational flows are used to assess the investment alternatives in this biogas plant optimization approach. Thus, bilateral connections have to be considered between the two planning levels. (Fleischmann and Koberstein, 2015) In order to derive the SBPP model, firstly the deterministic linear programming model OBPP, which supports the optimization of an operational schedule of a biogas plant when the structural decision is assumed as having been made is introduced. (Section 3.4.3) This model can be solved for one specific plant design and one specific scenario to derive the optimal plant schedule for these input data. The OBPP model is the basis of the SBPP model in which operational plant schedules are optimized for several plant designs and several price scenarios. (Section 3.4.4) Thus, the scenario optimal plant design can be determined. For every scenario i the scenario-optimal investment alternative $j(i)$, which is called a “strategy”, and its optimal net present value NPV^*_{ji} are determined. For all strategies, i.e. for all scenario-optimal investment alternatives $j(i)$, the net present value NPV_{jk} of investment alternative $j(i)$ and all other scenarios $k \neq i$ is determined. (By solving the SBPP model with fixed investments $j(i)$ for the input data of scenario k.)

All of the solutions are compared in a solution matrix. (Section 3.5.4, Table 3.12) This solution matrix is characterized by one optimal solution per scenario – i.e. NPV^*_{ji}. Note that different scenarios may point to the same optimal strategy (e.g. scenarios 1 and k of Figure 3.10 to the same optimal strategy $j(1) = j(k)$), thus resulting in $J' \leq I$ scenario-optimal strategies. In addition, the net present values for non-optimal scenario-strategy combinations are included – i.e. NPV_{jk}. A robust solution concerning all scenarios should be determined, because some scenario-optimal decisions, for example concerning a high investment, can ruin the biogas plant operator in the event of a worst case scenario. This risk should be avoided. The robust solution is extracted by using the rules of decision theory. As high solution robustness for a risk-averse decision maker should be reached, the decision rules of Hurwicz with a small lambda and the Maximin rule are used. (Section 3.5.4), (Scholl, 2001; Hurwicz, 1951) Both decision rules are characterized by a great solution robustness. Thus, the determined decisions can be considered as robust. (Scholl, 2001)

3.4.2 Assumptions concerning OBPP and SBPP

As an Operations Research model is only an abstraction of a real world decision, several assumptions concerning the modeling framework have to be made. The objective of the SBPP model is to determine the optimal investment strategy concerning biogas storages and CHP plant extensions. As declared in Section 3.2.2, this seems the easiest way to make the plant more flexible. A planning horizon of T periods which is subdivided into $t = 1...,T$ non-overlapping sub-periods is assumed. Only one specific biogas plant, located in Germany, is investigated.

The problem setting is as follows: a conventional biogas plant, which has a steady gas generation in the digester is assumed. As there are no gas storage capacities available within the plant, the power generation is also steady and totally inflexible. The generated power is sold by taking the EEG feed-in tariff. Moreover, as it is required by the German law, the waste heat is used for other processes.

Furthermore, there are several assumptions concerning the chosen marketing channel. As mentioned, there are several possibilities for biogas plant operators in Germany to participate in the energy market. It is assumed that the investigated biogas plant is an already existing plant in Germany, which is less than 20 years in operation. Only direct marketing at the day-ahead market is considered in the optimization approach. Hence, as explained in Section 3.2.3, it is possible to sell generated power in blocks of one hour the next day. As only one specific biogas plant is considered, an unlimited demand, or in other words a price-taker model, is assumed. The reason is that the energy supply of one biogas plant is very small compared to the total energy demand. Moreover, for the same reason, the amount of produced energy in the considered biogas plant has no impact on the spot market prices. Additionally, the market premium and the flexibility premium are, as offered by the German government in the current EEG and already mentioned in Sections 3.2.3 and 3.2.4, considered. For discounting an interest rate of i per period is assumed with $0 < i < 1$.

Concerning the biogas plant, there are several other assumptions. Firstly, it is assumed that the digester produces a steady amount of gas during the hours of a year. After the investment, this gas could be burned directly in the CHP plants, could be stored in a newly installed gas storage or be burned in a torch without generating revenues. As declared in Section 3.2.2, these are the characteristics of biogas plants with a type II configuration. Secondly, at the beginning of the planning horizon no storage capacities are available, thus the gas storage level is zero. Restrictions concerning the amount and point in time of starts of the CHP plants are not considered.

Within the OBPP model, an already flexibilized type II biogas plant with storage capacities is assumed. Thus, three types of gas flows are resulting, which can exist simultaneously and are depicted in Figure 3.11. One gas flow from the digester into the gas storage ($X_s^{DS} \geq 0$), one from the digester to the torch ($X_s^{DT} \geq 0$) and one from the storage to the CHP plant(s) ($X_s^{SC} \geq 0$). Additionally, the filling level of the gas storage is included ($X_s^S \geq 0$).

Finally, there are some assumptions concerning the characteristic of the investment, which are only considered in the SBPP model. For increasing the flexibility of the biogas plant several possible investment alternatives are distinguished. To increase the flexibility it is necessary to increase the electrical capacity by installing (an) additional CHP plant(s). Here, a finite number of discrete CHP plant capacities is considered. Furthermore, it is

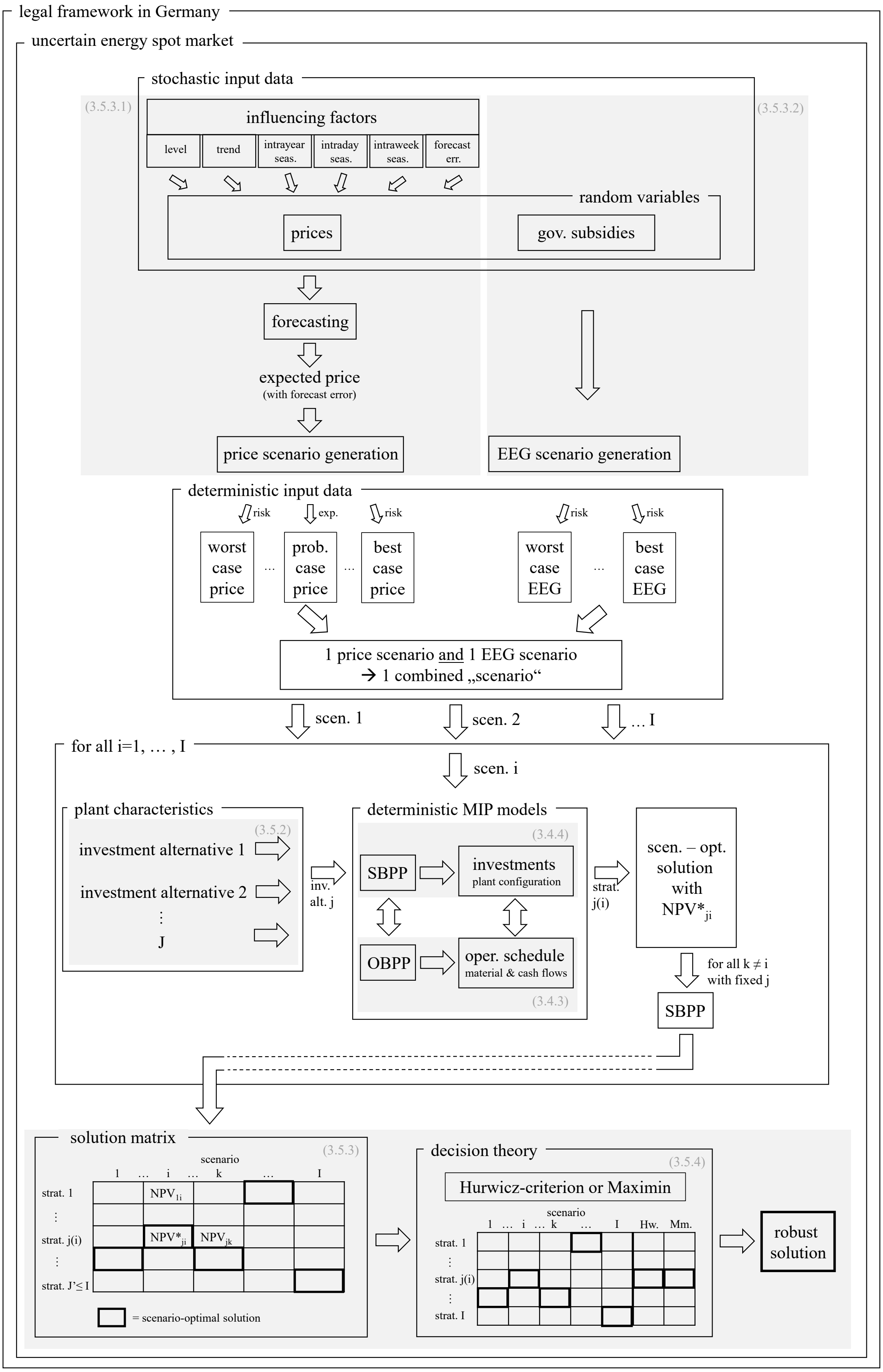

Figure 3.10: Graphical illustration of the solution approach

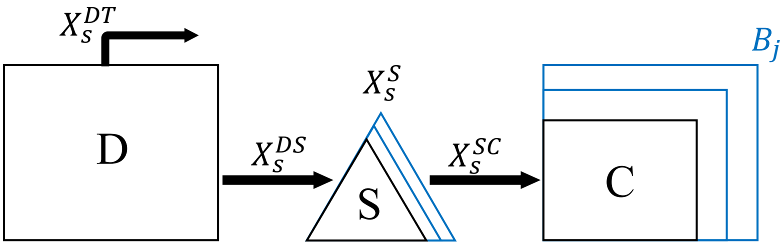

Figure 3.11: Structural and operational variables

necessary to create a possibility to store biogas, which is produced in the digester but not directly burned within the CHP plants or in the torch. For this reason, the gas and power production can be decoupled. Similar to the CHP plant capacity, a finite number of discrete storage capacities is considered. It is assumed that with an increase in the storage size economies of scale concerning the supply costs can be achieved. To install and operate the new technologies it is further necessary to invest in other infrastructure components like the foundation for the storage, gas lines, or a transformer with larger capacity. It is assumed that these infrastructure investments are fixed for all combinations of investment alternatives, but are only made if a storage or an additional CHP plant is installed. Therefore, the compatible combination of a gas storage, a CHP plant extension and further infrastructure components is represented by a (combined overall) investment alternative j with $j = 1, ..., J$. The choice of investment alternatives is then represented by the binary decision variable B_j. For all investments, an expected operation time of DeT periods is assumed. If the planning horizon is shorter than this operation time ($DeT > T$), the terminal value of the total investment is calculated by reducing balance depreciation. The resulting plant design, the operational flow variables, which are the same as in the OBPP model, and the structural investment decision variables are shown in Figure 3.11.

3.4.3 Operational biogas plant optimization problem – OBPP

Within the explanations to Figure 3.10 was specified that an optimized operational biogas plant schedule is used to asses the investment strategy. The OBPP model, which is used to optimize this operational plant schedule, is developed in the upcoming Section. As a basic design for the optimization of an operational schedule, a flexibly schedulable plant is assumed. This means that in the plant additional flexible CHP plant capacity and a biogas storage are implemented. Only if the biogas plant is flexibly schedulable, a direct marketing of the produced energy at the power exchange can be beneficial. Within the optimization process, two characteristic tradeoffs have to be considered during the profit maximization. The first tradeoff is to produce electricity in a current period out of the available biogas or to store the biogas for later periods. This decision depends on the current spot market price and thus the current possible payments, the available capacity in the biogas storage and the expectation regarding future spot market prices and thus the forecasted possible payments. The second tradeoff is to produce electricity in a current period or not to produce, to save up flexible excess capacity. As the flexibility premium compensates the flexible excess capacity, which is the unutilized share of the total capacity, the biogas plant operators have an incentive not to maximize the utilization of the CHP plants. The functionality of the flexibility premium is explained in Sections 3.2.3 and 3.2.4. However again in brief, the flexibility premium rewards the flexibility potential of a biogas plant. Hence, if in a biogas plant no electricity is produced in several periods, the remaining capacity on average and thus its flexibility potential increases. Hence, the payments of the flexibility premium increase as well. This decision depends not only on the current spot market price but also on the flexibility premium, which is a governmental subsidy. Managing those two tradeoffs simultaneously is not straightforward.

The optimization of the future operational schedule of the plant gives an idea of possible future cash flows. This information can also be used to assess an investment. The problem setting of the biogas plant is as given in Figure 3.11, but the decision about the binary variables is assumed as having been made. This means that one investment strategy is already chosen. Accordingly, the biogas plant design is given as flexible type II. As it is shown in Table 3.5, two different time grids are necessary to model the operational planning problem. Microperiods $s = s, ..., S$, which are given in hours, and macroperiods $t = t, ..., T$, which represent years, are distinguished. This is necessary, because the sales and payments at the spot market occur hourly, but the payments of the flexibility premium depend on the yearly production and are paid once at the end of a year. All microperiods are given by the set Φ. Additionally, the set $\Phi_t \subset \Phi$ is used to determine, which microperiod is in which macroperiod and the set $\Phi_t^* \in \Phi$ denotes the last microperiod of each macroperiod t in the planning horizon.

In order to determine the optimal plant schedule, several data is used. The efficiency a of the installed CHP plant(s) is given as the produced amount of electricity (measured in kWh) per Nm^3 biogas. To fulfill the requirements of the flexibility premium it is important as well to define the previously realized output of the biogas plant Bem^{init} in kWh per macroperiod (kWh/y). Additionally, two different types of variable costs are distinguished. The electricity production costs c^E (EUR/kWh) and the biogas production costs c^G (EUR/Nm^3). The biogas production costs include typical variable costs for the substrate, the fermentation process and personnel. The electricity production costs consist of costs for the combustion process. As the planning problem is capacitated, it is necessary to distinguish capacities for the gas storage Cap^S (Nm^3), and the CHP plants. Here, the formerly installed CHP plant capacity Cap^C (kWh) and the additionally installed CHP plant capacity Cap^{Cadd} (kWh) are differentiated. The distinction between Cap^C and Cap^{Cadd} is not necessary within the OBPP model. However, as this model should be extended later on and this differentiation is necessary then, it is distinguished at this point as well. The steady biogas production rate of the digester is defined as dp (Nm^3/h). For the sold electricity market premiums m_s (EUR/kWh) and spot market prices p_s (EUR/kWh) can be achieved.

The objective of the OBPP model is to maximize the resulting profit. Therefore, the following decision variables have to be optimized. Besides the market premium and the spot market prices, the flexibility premium constitutes an important part of the possible revenues. The granted flexibility premium payments per period s within the planning horizon are represented by $pr_s \geq 0$. The biogas plant operator can decide if the flexibility premium is requested or not, because the possible revenues are linked with the requirements described in Section 3.2.4.1. The decision is represented by the binary decision variable $Y_t \in \{0, 1\}$, which is 1 if the flexibility premium in macroperiod t is requested and 0 otherwise. Hence, the planning horizon for the operational scheduling model has to be several years and cannot be shorter. This is a special property of the developed approach, because it considers an operational schedule on a more mid-term than the common short-term level.

In order to optimize the operational plant schedule it is necessary to optimize several operational variables. Here, the gas flow from the digester to the torch $X_s^{DT} \geq 0$, the gas flow from the digester to the gas storage $X_s^{DS} \geq 0$, the gas flow from the gas storage to the CHP plants $X_s^{SC} \geq 0$ and the gas storage level $X_s^S \geq 0$ are distinguished.

Table 3.5: Notation OBPP

Indices	
$s = 1,...,S$	microperiods, hours (h) in the planning horizon
$t = 1,...,T$	macroperiods, years (y) in the planning horizon
Sets	
Φ	set of all microperiods
$\Phi_t \subset \Phi$	set of all microperiods in macroperiod t
$\Phi_t^* \in \Phi$	last microperiod in macroperiod t
Parameters	
a	efficiency of the installed CHP plants / produced amount of electricity per Nm^3 biogas in kWh/Nm^3
Bem^{init}	previously realized output per macroperiod kWh/y
c^E	electricity production costs of a specific biogas plant (variable costs) EUR/kWh
c^G	biogas production costs of a specific biogas plant (variable costs) EUR/Nm^3
Cap^S	installed capacity of a gas storage in Nm^3
Cap^C	formerly installed CHP plant capacity (maximum amount of electricity produced in one hour) in kWh
Cap^{Cadd}	additionally installed CHP plant capacity (maximum amount of electricity produced in one hour) in kWh
dp	steady gas production rate of the digester in Nm^3/h
Max^P	sufficiently large number
m_s	market premium in microperiod s in EUR/kWh
p_s	spot market price forecast at the power exchange in the day-ahead market in microperiod s in EUR/kWh
Variables	
$pr_s \geq 0$	granted flexibility premium in microperiod s in EUR paid once in a year (EUR/y)
$X_s^{DT} \geq 0$	gas flow from digester to the torch in microperiod s in Nm^3
$X_s^{DS} \geq 0$	gas flow from digester to the gas storage in microperiod s in Nm^3
$X_s^{SC} \geq 0$	gas flow from the gas storage to the CHP plants in microperiod s in Nm^3
$X_s^S \geq 0$	gas storage level at the end of microperiod s in Nm^3
$Y_t \in \{0,1\}$	decision variable, 1 if the flexibility premium in macroperiod t is requested, 0 otherwise

3.4.3.1 Objective function

The objective of the model is to maximize the total profit consisting out of several payments and payouts. Therefore, the objective function consists out of four parts, which are explained in detail later on. In the first part, the spot market payments (SMP_s) are considered. Within the second part, the variable electricity generation payouts ($VEGP_s$) are modeled. The third part represents the realized subsidy payments (RSP_s) based on the flexibility premium. As a last part, the torch payouts (TP_s) are modeled. As all of the four parts represent the payments and payouts per microperiod, they have to be summed up for all microperiods s.

$$Max \quad \sum_s \underbrace{(p_s + m_s) \cdot a \cdot X_s^{SC}}_{SMP_s} - \underbrace{(c^E \cdot a + c^G) \cdot X_s^{SC}}_{VEGP_s} + \underbrace{pr_s}_{RSP_s} - \underbrace{c^G \cdot X_s^{DT}}_{TP_s} \tag{3.1}$$

The first part of the objective function is represented by the spot market payments (SMP_s). Here, the sum of the spot market price p_s in a specific microperiod s and the market premium m_s is in any microperiod s multiplied with the amount of produced electricity. The amount of produced electricity is given by the gas flow in microperiod s from the biogas storage to the CHP plants X_s^{SC} multiplied with the CHP plant's efficiency. The functionality of the market premium, which is a governmental subsidy, is stated in Subsection 3.2.4.1.

The second part of the objective function is represented by the variable electricity generation payouts ($VEGP_s$). Here, similar to the spot market payments, the variable electricity production costs per kWh of the specific biogas plant are multiplied with the amount of produced electricity in each microperiod s. The variable electricity production costs per kWh consist of the costs for the used biogas c^G multiplied with the production efficiency of the CHP plants and the costs for the combustion process of biogas into electricity c^E.

The third part of the objective function represents the realized subsidy payments (RSP_s) regarding the flexibility premium. This payment is executed only in the last microperiod s of a specific macroperiod or year t if the biogas operator requests it. The calculation of the granted flexibility premium payment in a microperiod s is explained in detail in Constraints (3.7a) to (3.7d).

The fourth part of the objective function represents the costs for using the torch. If it is not beneficial to produce electricity and the biogas storage is completely filled, there is the possibility to burn biogas using the torch. No payments are generated when the biogas is burned through the torch. However, the generation of the biogas causes production costs (c^G). Hence, these costs have to be considered as payouts within the objective function.

3.4.3.2 Constraints

Plant characteristic

$$dp = X_s^{DS} + X_s^{DT} \qquad \forall s \quad (3.2)$$

One of the assumptions of the OBPP model is that the digester produces a steady amount of gas during the microperiods because a type II biogas plant is considered. Thus, the biogas production rate cannot be influenced or stopped. This assumption is an abstraction of the real world to avoid the complex modeling of non-linear biogas production rates before and after a stop of the digestion processes. This assumption is modeled in Constraint (3.2). At this point, the gas flow from the digester into the gas storage (X_s^{DS}) plus the gas flow from the digester to the torch (X_s^{DT}) have to equal the gas production (dp) in each microperiod. As all of the produced biogas is either burned in the torch or filled in the storage and further combusted in the CHP plant(s), Constraint (3.2) together with $VEGP_s$ and TP_s show that for every Nm^3 of produced biogas at least the biogas production costs c^G have to be paid. Hence, the biogas production costs are not relevant for the decision of the operational biogas plant schedule, because the digestion processes cannot be stopped due to the assumptions. However, this model should be extended later on for the biogas plant design investment decision; for this reason, these costs are considered in the OBPP model as well. In the extended model, those costs are necessary to decide whether the net present value, which will be the objective value in this model, is positive or negative. Nevertheless, they will not influence the operational schedule in the subsequent model.

Capacity restrictions

$$X_s^{SC} \cdot a \leq Cap^C + Cap^{Cadd} \qquad \forall s \quad (3.3)$$

Constraint (3.3) ensures that the amount of produced electricity per hour does not exceed the already available capacity plus the additional electrical capacity. The amount of produced electricity is calculated by multiplying the amount of gas flow from the storage to the CHP plants (X_s^{SC}) with the efficiency coefficient (a) of the installed CHP plants.

$$X_s^S \leq Cap^S \qquad \forall s \quad (3.4)$$

Constraint (3.4) ensures that the gas storage level (X_s^S) at the end of each microperiod does not exceed the gas storage capacity.

$$\sum_{s\in\Phi_t} a \cdot X_s^{SC} \leq Bem^{init} + (1-Y_t) \cdot Max^P \qquad \forall t \quad (3.5)$$

As it is required by the current version of the EEG and already mentioned during the explanations regarding the flexibility premium, it is prohibited that the realized output of the biogas plant in each macroperiod t after an increase in electrical capacity is higher than the previously realized output, if a biogas plant operator requests the flexibility premium. That means, if the flexibility premium is requested, the produced amount of electricity in total in a macroperiod has to be lower than or equal to the realized output in the period before the investment was made. However, the increase in electrical capacity gives the biogas plant operators the opportunity to produce more electricity in beneficial periods. This restriction, modeled in Constraint (3.5), is used to ensure that the plant operators reserve flexible capacity of their additionally installed electrical capacity. Constraint (3.5) serves not as a restriction, if the flexibility premium is not requested ($Y_t = 0$). However, the amount of produced electricity is then restricted by the capacity Constraint (3.3).

$$\sum_{s\in\Phi_t} \frac{a \cdot X_s^{SC}}{|\Phi_t|} \geq \frac{1}{5} \cdot (Cap^C + Cap^{Cadd}) \cdot Y_t \qquad \forall t \quad (3.6)$$

In addition to the upper bound of the realized output of the biogas plant, there is a lower bound given by the EEG. In any year the biogas plant operator wants to request the flexibility premium, the realized output on average per microperiod s of the biogas plant has to be at least $\frac{1}{5}$ of the installed electrical capacity. Thus, the realized output per year t ($\sum\limits_{s\in\Phi_t} a \cdot X_s^{SC}$) is divided by the assumed number of microperiods in a macroperiod ($|\Phi_t|$) to calculate the realized output on average per microperiod s in a macroperiod t. If the realized output was smaller, the flexibility premium would not be granted for the expired year.

$$pr_s \leq \begin{cases} \left(Cap^C + Cap^{Cadd} - \sum\limits_{s\in\Phi_t} \dfrac{a \cdot X_s^{SC}}{|\Phi_t|} \cdot 1.1\right) \cdot 130 & \forall s \in \Phi_t^* \quad (3.7a) \\ (Cap^C + Cap^{Cadd}) \cdot 0.5 \cdot 130 & \forall s \in \Phi_t^* \quad (3.7b) \\ Max^P \cdot Y_t & \forall s \in \Phi_t^* \quad (3.7c) \\ 0 & \forall s \notin \Phi_t^* \quad (3.7d) \end{cases}$$

The calculation of the granted flexibility premium payment in a microperiod s is explained in Constraints (3.7a) to (3.7d). The decision about requesting the flexibility premium or not is modeled using the binary variable Y_t. If the biogas plant operator decides not to request the flexibility premium, the binary variable is set to zero. Accordingly, Constraint (3.7c) would restrict the premium payment pr_s to zero as well. If the biogas plant operator requests the flexibility premium, the premium payment is, according to Constraint (3.7c), not restricted. Hence, Constraint (3.7a) would restrict the premium payment and the flexibility premium payment would be calculated as it is required by the current version of the EEG (EEG, 2017) and modeled in Constraint (3.7a). The last microperiod in a macroperiod t is given by set Φ_t^*. First, the flexible excess capacity per average microperiod s in a macroperiod t has to be calculated as in Constraint (3.6). Afterward, this realized output on average is rated with a correction factor of 1.1 for biogas plants, which is defined by the German legislation, and subtracted from the sum of the installed capacity ($Cap^C + Cap^{Cadd}$). The resulting flexible excess capacity for an average microperiod is compensated with 130 $EUR/kWhy$. Aforementioned, the flexibility premium payment is only executed in the last microperiod of a macroperiod t. Thus, the calculations according to Constraints (3.7a) to (3.7c) are only made for those microperiods s, which are the last microperiod in a macroperiod. In all other periods, the flexibility premium payments are set to zero. (see (3.7d)) The flexible excess capacity is restricted to a maximum of the half of the installed electrical capacity by the EEG. This restriction is modeled in Constraint (3.7b). To understand the function of the flexibility premium it is important to know that it is not allowed to use the additional installed capacity continuously. The realized output of the current year has to be lower or equal than the previously realized output per year as mentioned in Constraint (3.5). If the requirements are met, the flexibility premium is granted for a ten years horizon. The functionality is explained in detail in Subsection 3.2.4.1.

Mass balance

$$X_s^S = X_{s-1}^S + X_s^{DS} - X_s^{SC} \qquad \forall s \quad (3.8)$$

The storage process of produced but not yet burned biogas is modeled in Constraint (3.8). Here, as usual, the gas storage level (X_s^S) at the end of a microperiod s has to equal the gas storage level of the previous microperiod, plus the gas flow into the gas storage from the digester (X_s^{DS}), minus the gas flow from the gas storage to the CHP plants (X_s^{SC}) in the current microperiod s.

Within the model, material flows and storage levels can only take non-negative real values. Binary variables represent the decisions whether the flexibility premium is requested or not.

3.4.4 Strategic biogas plant optimization problem – SBPP

As declared, the main objective is to support the investment decision of adjusting the design of a conventional biogas plant into a flexible type II plant considering uncertain revenues. In order to model this decision the previously developed OBPP model for the optimization of an operational plant schedule, described in Section 3.4.3, has to be extended. Within the SBPP model, the plant design is no longer assumed as having been fixed. Instead, the design should be optimized. As the model to optimize the operational schedule of a biogas plant has been explained in detail in the previous section, only the new and adjusted parts of the model are described in the current one.

In order to model the extensions of the investment decision, further indices, parameters and variables are necessary. The additional and adjusted notation is provided in Table 3.6. The index j is used to distinguish between several possible investment alternatives. Those alternatives consist of a biogas storage with a specific size and a specific CHP plant extension capacity. The known parameters Cap^S and Cap^{Cadd} are adjusted to Cap_j^S and Cap_j^{Cadd} because in the SBPP model they depend on the chosen investment alternative. The aim is to decide which plant design is beneficial. Therefore, the specific total investments are rated with I_j, which are quantity-independent fixed costs that are payed once. Further, if reducing balance depreciation is used to calculate the terminal value of the total investment at the end of the planning horizon, the depreciation rate per year dr_s with $s \in \Phi_t^*$ has to be defined. Moreover, as payments and payouts at different points in time have to be compared and thus discounted, it is necessary to define the discounting interest rate as i. To distinguish between the several investment alternatives the binary variable $B_j \in \{0,1\}$ is used. The variable is 1 if investment alternative and thus strategy j is chosen and 0 otherwise. The known variable Y_t is adjusted to $Y_{j,t} \in \{0,1\}$. Accordingly, the binary decision variable is 1 if the investment strategy j is chosen and the flexibility premium is requested in year t and 0 otherwise. $Y_{j,t}$ models whether the flexibility premium is requested under the condition of an already chosen investment strategy which is represented by B_j. Within the following Subsections 3.4.4.1 and 3.4.4.2 the extended model is described.

Table 3.6: Additional and adjusted notation SBPP

Indices	
$j = 1,...,J$	discrete investment alternatives
Parameters	
Cap_j^S	installed capacity of a biogas storage in investment alternative j in Nm^3
Cap_j^{Cadd}	additionally installed CHP plant capacity in investment alternative j in kWh
dr_s	decreasing depreciation rate per year t in microperiod $s \in \Phi_t^*$
i	discounting interest rate per microperiod
I_j	total investment for investment alternative j in EUR
Variables	
$B_j \in \{0,1\}$	decision variable, 1 if investment alternative (strategy) j is chosen, 0 otherwise
$NPV \geq 0$	objective value
$Y_{j,t} \in \{0,1\}$	decision variable, 1 if the flexibility premium in macroperiod t is requested and investment alternative (strategy) j is chosen, 0 otherwise

3.4.4.1 Objective function

In contrast to the previously explained OBPP model, the objective value of the SBPP model is defined as a result of discounted payments and payouts. Thus, the objective value represents the NPV. The understanding of the NPV is similar to common definitions, which are among others given by Hübner (2007). The payments and payouts appear at different points in time. In order to make the investment strategies comparable, the resulting payments and payouts are discounted. Hence, the objective function of the current SBPP model consists out of five parts. The spot market payments (SMP_s), the variable electricity generation payouts ($VEGP_s$), realized subsidy payments (RSP_s) and torch payouts (TP_s) are modeled similar to the OBPP model. For this reason, they are not explained in detail again. The detailed explanations are given in Section 3.4.3. The only difference is that they have to be discounted using the interest rate i. Additionally, the total loss of value (LOV) is considered in the last part of the objective function.

$$Max \quad NPV =$$
$$\sum_j \sum_s \frac{(p_s + m_s) \cdot a \cdot X_s^{SC} - (c^E \cdot a + c^G) \cdot X_s^{SC} + pr_s - c^G \cdot X_s^{DT}}{(1+i)^s} - \underbrace{\frac{dr_s}{(1+i)^S} \cdot B_j \cdot I_j}_{LOV} \tag{3.9}$$

The only new part is representing the total LOV of the chosen investment. This loss can be calculated as the discounted sum of all yearly depreciations during the planning horizon. The payout of the initial investment depends on the chosen plant design, which is determined by the structural decision variable B_j. The yearly depreciation is calculated by reducing balance depreciation for the length of the planning horizon as it is given in Equation (3.9). Here, the yearly depreciation rates are multiplied with the initial investment, depending on the chosen investment strategy, and then discounted. These yearly discounted depreciations are summed up for all years of the planning horizon ($t = t, ..., T$ with $T < DeT$). In order to achieve this, the depreciations, which are defined for each microperiod, are summed up only for the last microperiods in a macroperiod. ($s \in \Phi_t^*$)

3.4.4.2 Constraints

Constraints (3.2) and (3.8) remain the same as in the OBPP model. All other constraints are adjusted or added in contrast to the OBPP model and thus are explained in detail.

Design configuration

$$\sum_j B_j = 1 \tag{3.10}$$

$$Y_{j,t} \leq B_j \qquad \forall j,t \tag{3.11}$$

In Constraints (3.10) and (3.11) the plant design decision is restricted. It is only permitted to choose one investment strategy or in other words one combination of an additional CHP plant version and one storage version each. Additionally, the two binary variables B_j and and $Y_{j,t}$ have to be connected, because it is only possible to request the flexibility premium subject to an investment strategy j, if the strategy is already chosen.

Capacity restrictions

$$X_s^{SC} \cdot a \leq Cap^C + \sum_j B_j \cdot Cap_j^{Cadd} \qquad \forall s \tag{3.12}$$

Constraint (3.12) ensures that the amount of produced electricity per hour does not exceed the already available capacity plus the additional electrical capacity. The additional electrical capacity depends on the chosen investment strategy.

$$X_s^S \leq \sum_j B_j \cdot Cap_j^S \qquad \forall s \tag{3.13}$$

Constraint (3.13) ensures that the gas storage level (X_s^S) in each microperiod does not exceed the chosen gas storage capacity. The gas storage capacity depends on the chosen investment strategy.

$$\sum_{s \in \Phi_t} a \cdot X_s^{SC} \leq Bem^{init} + (1 - \sum_j Y_{j,t}) \cdot Max^P \qquad \forall t \tag{3.14}$$

Constraint (3.14) is similar to Constraint (3.5) of the previously explained OBPP model and restricts the realized output to an upper bound. As the decision variable $Y_{j,t}$ now represents the decisions regarding requesting the flexibility premium and the choice of investment strategies, the variables have to be summed up over all investment alternatives j. The remaining parts of the constraint are equal to (3.5).

$$\sum_{s\in\Phi_t} \frac{a \cdot X_s^{SC}}{|\Phi_t|} \geq \frac{1}{5} \cdot \sum_j \left(Cap^C + Cap_j^{Cadd}\right) \cdot Y_{j,t} \qquad \forall t \quad (3.15)$$

As mentioned during the explanation of the OBPP model, the realized output of the biogas plant has to be at least $\frac{1}{5}$ of the installed electrical capacity in any year, the biogas plant operator wants to request the flexibility premium. Otherwise, the flexibility premium is not granted for the expired year. The totally installed electrical capacity depends on the chosen investment strategy and is, as well as the decision about requesting the flexibility premium, represented by the binary decision variable $Y_{j,t}$.

$$pr_s \leq \begin{cases} \left(Cap^C + \sum_j B_j \cdot Cap_j^{Cadd} - \sum_{s\in\Phi_t} \frac{a \cdot X_s^{SC}}{|\Phi_t|} \cdot 1.1\right) \cdot 130 & \forall s \in \Phi_t^* \quad (3.16a) \\ \left(Cap^C + \sum_j B_j \cdot Cap_j^{Cadd}\right) \cdot 0.5 \cdot 130 & \forall s \in \Phi_t^* \quad (3.16b) \\ \sum_j Max^P \cdot Y_{j,t} & \forall s \in \Phi_t^* \quad (3.16c) \\ 0 & \forall s \notin \Phi_t^* \quad (3.16d) \end{cases}$$

The calculation of the yearly flexibility premium payment is similar to Constraints (3.7a) to (3.7d) of the previously explained OBPP model. The difference is that in the SBPP model the flexible excess capacity depends on the chosen investment strategy. Hence, the binary decision variable B_j is used to determine which additional electrical capacity is chosen and thereby determines the total excess capacity. Additionally, the definition of the variable $pr_s \geq 0$ has to be adjusted as it depends on the electrical excess capacity. As the possible investment alternatives are all considered implicitly within the calculation of pr_s, no index j is necessary. In Constraint (3.16c) the binary decision variables $Y_{j,t}$ have to be summed up for all investment alternatives j, because the choices regarding requesting the flexibility premium and investment strategies are considered in $Y_{j,t}$.

Within the model, material flows and storage levels can only take non-negative real values. Binary variables represent the decisions whether an investment strategy j is chosen or not and whether the flexibility premium is requested or not.

3.5 Application of the deterministic SBPP model in an uncertain environment

In Section 3.5 the deterministic SBPP model is applied in an uncertain environment as it has been explained in Figure 3.10. Therefore, the relevant uncertainties are modeled in a first step in Section 3.5.1. Afterward, the experimental design is defined in Section 3.5.2. The effects of uncertainties are analyzed in Section 3.5.3 before a robust investment decision is made in Section 3.5.4.

3.5.1 Modeling uncertainty

As mentioned in Section 3.2.4, the total revenues a biogas plant operator can generate using direct marketing consist out of several parts. As a first part revenues are generated at the chosen spot market, depending on the spot market prices. It is possible to sell the produced energy on several spot markets simultaneously. Thus, the total spot market revenues consist out of the spot market prices of the chosen markets. The second part are revenues out of subsidies. As explained in Section 3.2.4.1, it is possible to request two subsidies, if the produced energy is sold through direct marketing – the market premium and the flexibility premium.

For all of those parts of the total revenues, it has to be separately forecasted whether there is relevant uncertainty in the revenues or not, in order to reveal the effect of the uncertainty in a second stage. The characterization of the uncertainties is explained in the upcoming subsections.

3.5.1.1 Spot market price forecast

The fluctuations and seasonalities within the spot market prices are mentioned in Section 3.2.4.2. As explained, the spot market prices can be characterized using three different seasonalities, intrayear, intraweek and intraday, and a currently decreasing trend. Using the knowledge of those characteristics, it is assumed that the time series of spot market prices at the day-ahead market for the upcoming five years can be approximated using the following model:

$$p_s = a + b \cdot s + c_s^Y + c_s^W + c_s^D + u_s \tag{3.17}$$

Within this model, p_s is defined as the spot market price in a microperiod s. The model is built using time series decomposition. Hence, a is defined as a level component, b as a trend component and the three remaining parameters c_s^Y, c_s^W, c_s^D characterize the intrayear, intraweek and intraday seasonalities. u_s is defined as the white noise which cannot be forecasted. As one can see, all of the above mentioned characteristics of the spot market prices are covered within (3.17).

As usual in time series analysis, the component parameters of the forecasting model have to be forecasted. (Makridakis et al., 2010) Hence, the forecast can be wrong because of unexpected future changes in the environment of the energy market. The quality of the forecast, or in other words the forecast error, is represented by the the difference between the real value p_s of a microperiod s and its forecast $\hat{p}_s$ where $\hat{p}_s := \hat{a} + \hat{b} \cdot s + \hat{c}_s^Y + \hat{c}_s^W + \hat{c}_s^D$ and where $\hat{a}, \hat{b}, \hat{c}_s^Y, \hat{c}_s^W$ and $\hat{c}_s^D$ denote the forecasts of the component parameters. In general, it is unrealistic to assume that a forecast without a forecast error can be reached. For this reason, it is important to analyze the effect of a potential forecast error on the decision and the resulting outcome.

As can be seen, all of the component parameter values are uncertain themselves, because every characteristic of the spot market prices can be subject to change separately. For example, it could be possible that the trend component is changing. Although, the current trend is decreasing, it is not completely unlikely that the prices will increase in the future. Keles et al. (2011) distinguish several scenarios for the future energy price development. What all the mentioned scenarios have in common is that the energy prices will increase, thus this could be a future development. As the intrayear and intraweek seasonalities are mainly based on the characteristic of the energy demand, it can be assumed that they will remain similar in the future. This assumption is based on the conclusions that for instance the intrayear seasonality is based on the climatic environment in Germany. The climate will probably not change significantly within the planning horizon of the current model. However, for single years there could be a significant change within the intrayear price seasonality. For example because of extreme weather situations like unusual hot and dry periods in a year. Moreover, the intraweek seasonality is mainly based on the difference in demand between weekdays and weekends because of the reduced industrial production during the weekend. It is unlikely that this behavior will change in the nearer future as well. Moreover, the average level of the spot market prices (a) can be subject to changes as well. For instance, it is possible that the level will be lower in the future because of the ongoing decreasing trend.

3.5.1.2 Flexibility premium

Apart from the spot market revenues, important parts of the generated total revenues using direct marketing are subsidies. Aforementioned in Section 3.2.4.1, it is possible to request the market and flexibility premium.

The market premium is not characterized by significant uncertainty. As explained previously, biogas plants are regulated using the EEG version, which was the current version when a biogas plant was put into operation. Hence, the legal framework cannot be changed for existing plants and the operators have the guarantee of a 20-year entitlement on this subsidy. Nevertheless, in a new amendment of the EEG the market premium could be canceled, which affect operators who want to build a new biogas plant. Because of the assumption of only analyzing already built and running plants in this optimization approach, there is no considerable uncertainty regarding the market premium.

Similar to the market premium, the flexibility premium is certain if it is granted once, but only for a 10 years horizon. However, as mentioned in Subsection 3.2.4.1, there are plenty of requirements to be met to successfully request the flexibility premium. If at least one requirement is not fulfilled, the flexibility premium would not be granted. Hence, the payments of the flexibility premium are subject to uncertainty.

3.5.2 Experimental design

In order to verify the performance of the developed SBPP model in an uncertain environment a numerical experiment for a fictional but close to reality biogas plant is generated. This biogas plant is less than 20 years in operation. The specific biogas plant characteristics are depicted in Table 3.7. A rather medium biogas plant with a steady gas production rate of 700 Nm^3/h and a currently installed CHP plant capacity of 1500 kWh is assumed. Furthermore, a rated output of 75 % of the currently installed capacity is presumed. One Nm^3 biogas can be used to produce 1.52858 kWh of electricity. Moreover, the biogas and electricity production costs of the analyzed biogas plant are ascertained with $c^G = 0.08\ EUR/kWh$ and $c^E = 0.02\ EUR/kWh$. For discounting an interest rate of 2.76 % is assumed. (Deutsche Bundesbank, 2017) In order to calculate the terminal value at the end of the planning horizon, reducing balance depreciation with a yearly depreciation rate dr_s with $s \in \Phi_t^*$ is used. As given in Table 3.7 the yearly depreciation rates start with 30 % in the first year and end up with 7 % in the fifth. This is justified by the reason that machines like CHP plants have a higher loss of value in the first years of operation.

Table 3.7: Biogas plant specific input data

a	1.52858 kWh/Nm^3				
Bem^{init}	75 % of Cap^C				
c^E	0.02 EUR/kWh				
c^G	0.12 EUR/Nm^3 (=0.08 EUR/kWh)				
Cap^C	1500 kWh				
dp	700 Nm^3/h				
i	2.76 % p.a.				
dr_s	0.30	0.21	0.15	0.10	0.07
s	1	2	3	4	5

It is explained in Section 3.4 that several discrete investment alternatives are distinguished within the developed optimization model. For the current calculations, 12 different storage versions and 12 different CHP plant versions are assumed. The specific capacities and the related amount of investments are shown in Table 3.8. The amount of investments for additional CHP plants is based on the published information by the FNR. (FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2017) The amount of investments for the biogas storages is based on prices from manufacturers. For both investment decisions is assumed that there is an alternative 1, which means that the plant design will not be changed. Furthermore, economies of scale are considered regarding the amount of the investments. In addition to the described investments, a fixed infrastructure investment of 220,000 EUR is considered within the model, if one of the storages and/or CHP plants is installed. As explained, an investment alternative is characterized by a combination of one CHP plant capacity extension and one biogas storage. Accordingly, using 12 different versions each, 144 investment alternatives would be possible. However, since there is additionally assumed that the size of the biogas storage has to be large enough compared to the CHP plant capacity to keep the plant at least two hours running, only 128 possible investment alternatives are remaining. The planning horizon (T) is 5 years. The investments depreciation time (DeT) is 10 years.

Table 3.8: Investment alternatives

j	Cap_j^S	C_j^{Cadd}	I_j	j	Cap_j^S	C_j^{Cadd}	I_j	j	Cap_j^S	C_j^{Cadd}	I_j
1	0	0	0	44	40	1.5	1507.8	87	40	3.5	2247.7
2	5	0	295	45	45	1.5	1517.8	88	45	3.5	2257.7
3	10	0	359	46	5	2	1530.6	89	10	4	2284.4
4	12	0	370	47	10	2	1594.6	90	12	4	2295.4
5	15	0	390	48	12	2	1605.6	91	15	4	2315.4
6	18	0	410	49	15	2	1625.6	92	18	4	2335.4
7	20	0	420	50	18	2	1645.6	93	20	4	2345.4
8	25	0	440	51	20	2	1655.6	94	25	4	2365.4
9	30	0	455	52	25	2	1675.6	95	30	4	2380.4
10	35	0	470	53	30	2	1690.6	96	35	4	2395.4
11	40	0	480	54	35	2	1705.6	97	40	4	2405.4
12	45	0	490	55	40	2	1715.6	98	45	4	2415.4
13	5	0.5	803.8	56	45	2	1725.6	99	10	4.5	2435.2
14	10	0.5	867.8	57	5	2.5	1720.3	100	12	4.5	2446.2
15	12	0.5	878.8	58	10	2.5	1784.3	101	15	4.5	2466.2
16	15	0.5	898.8	59	12	2.5	1795.3	102	18	4.5	2486.2
17	18	0.5	918.8	60	15	2.5	1815.3	103	20	4.5	2496.2
18	20	0.5	928.8	61	18	2.5	1835.3	104	25	4.5	2516.2
19	25	0.5	948.8	62	20	2.5	1845.3	105	30	4.5	2531.2
20	30	0.5	963.8	63	25	2.5	1865.3	106	35	4.5	2546.2
21	35	0.5	978.8	64	30	2.5	1880.3	107	40	4.5	2556.2
22	40	0.5	988.8	65	35	2.5	1895.3	108	45	4.5	2566.2
23	45	0.5	998.8	66	40	2.5	1905.3	109	10	5	2580
24	5	1	1087.9	67	45	2.5	1915.3	110	12	5	2591
25	10	1	1151.9	68	5	3	1896.7	111	15	5	2611
26	12	1	1162.9	69	10	3	1960.7	112	18	5	2631
27	15	1	1182.9	70	12	3	1971.7	113	20	5	2641
28	18	1	1202.9	71	15	3	1991.7	114	25	5	2661
29	20	1	1212.9	72	18	3	2011.7	115	30	5	2676
30	25	1	1232.9	73	20	3	2021.7	116	35	5	2691
31	30	1	1247.9	74	25	3	2041.7	117	40	5	2701
32	35	1	1262.9	75	30	3	2056.7	118	45	5	2711
33	40	1	1272.9	76	35	3	2071.7	119	10	5.5	2719.7
34	45	1	1282.9	77	40	3	2081.7	120	12	5.5	2730.7
35	5	1.5	1322.8	78	45	3	2091.7	121	15	5.5	2750.7
36	10	1.5	1386.8	79	10	3.5	2126.7	122	18	5.5	2770.7
37	12	1.5	1397.8	80	12	3.5	2137.7	123	20	5.5	2780.7
38	15	1.5	1417.8	81	15	3.5	2157.7	124	25	5.5	2800.7
39	18	1.5	1437.8	82	18	3.5	2177.7	125	30	5.5	2815.7
40	20	1.5	1447.8	83	20	3.5	2187.7	126	35	5.5	2830.7
41	25	1.5	1467.8	84	25	3.5	2207.7	127	40	5.5	2840.7
42	30	1.5	1482.8	85	30	3.5	2222.7	128	45	5.5	2850.7
43	35	1.5	1497.8	86	35	3.5	2237.7				

Cap_j^S in 1000 Nm^3; Cap_j^{Cadd} in 1000 kWh; I_j in 1000 EUR

The parameters of the previously developed forecasting model (Section 3.5.1.1) are forecasted from historical data of the day-ahead market prices during the years 2011 to 2014. The character of those prices is explained in Section 3.2.4. In that section, the prices from 2011 to 2015 are analyzed. In order to forecast and test the necessary parameters using time series decomposition, the available data of five years has to be divided into a learning and a test set. Thus, the years 2011 to 2014 are used as a learning set to find estimators for the parameters. Afterward, the performance of the estimators in the forecasting function is tested using data from 2015 by calculating the mean squared error (MSE). (Hüttner, 1986) It is possible to model all previously explained characteristics of the spot market prices this way. Nevertheless, a forecasting error appears. The distribution of the resulting forecasting errors is characterized by a normal distribution with an expected value $\mu = 0$ and standard deviation $\sigma = 10.409$. As the expected value of the resulting forecast error is zero, the standard definition of the coefficient of variation $\frac{\sigma}{\mu}$ cannot be applied to express the forecast quality. Thus, we set the forecast error of the previously mentioned price forecast in relation to the mean spot market price instead and denite this key performance indicator as cov. It serves as a percentage measure of forecast quality and of price uncertainty. By doing so, a cov = 0.3291 results. This low value of cov shows a low variation of the forecast errors and emphasizes the good quality of the forecast.

By varying cov, new time series forecasts - for example with a worse forecasting quality expressed by a higher cov - can be simulated. The time series, based on the previously explained optimized estimators, serves, in the remainder, as the *base scenario* to compare several scenario depending outcomes. That means that this time series shows the most probable development of the spot market prices (“probable case” in Figure 3.10), if there are no market influencing changes in the future. The influence of these changes is included using further scenarios (e.g., best and worst cases in Figure 3.10) and analyzed in the next section.

3.5.3 Effects of uncertainties

In order to analyze the effects of the examined uncertainties, several further scenarios are generated. In Section 3.5.3.1 a varying quality of the spot market price forecasts and varying characteristics of the forecast model's different parameters are simulated. Throughout this section, the "probable case EEG" (see Figure 3.10) is assumed to hold. At first, the uncertainty regarding the forecast error is modeled using scenarios. Hence, three scenarios are compared to measure the influence of the forecast error. As a first scenario, the original prices of the day-ahead market from 2011 to 2015 are used as input data. This scenario represents the case that a perfect forecast had been made. (cov = 0; "best case" scenario with respect to the forecast quality of spot market prices, see Figure 3.10) The second scenario represents the base scenario as constructed and explained in Section 3.5.2. (cov = 0.3291; most probable forecast quality of prices) As a third scenario, the estimators in the forecasting function, which is used to generate the base scenario, are adjusted in a way to increase the forecast error by 90 %. Thus, a very poor forecast is generated. (cov = 0.6251; worst case forecast quality of prices)

Next in Section 3.5.3.1, the already mentioned uncertainties regarding the specific component parameter values are investigated in some more detail. Therefore, at first, the level component parameter a is varied. Again, the idea is to simulate extreme scenarios like the best and worst case. Hence, the forecast $\hat{a}$ of the price level is in- and decreased by 90 % in order to derive a best and worst scenario. Similar scenarios are derived for the trend component b. Here, a 90 % in- and decrease of the forecast $\hat{b}$ of the trend component is distinguished. As the trend parameter represents a decreasing process, an increase of the trend component represents faster decreasing prices in the planning horizon. Additionally, a switched trend is considered. Therefore, the trend component is decreased through the first years of the planning horizon and afterward reversed into an increasing trend. Moreover, the uncertainty in each of the seasonality components is distinguished by a 90 % in- and decrease of the coefficients of variation of the seasonal parameters. The variation of the intraday seasonal parameter is exemplarily depicted in Figure 3.12. Here, the price curve within an exemplary week (from Monday to Sunday) is simulated for the original forecast and for the reduced resp. increased intraday seasonality. This way of generating scenarios is similar to the idea of Wichmann et al. (2018).

In Section 3.5.3.2, the influence of the uncertainty regarding the flexibility premium is analyzed. Here, only two scenarios are compared. Firstly, the best case (=base) scenario with granted flexibility premium is considered. Secondly, the same price data is used, but it is assumed that the flexibility premium is not granted. (worst case) Using all these developed scenarios, the effects of the explained uncertainties can be analyzed.

In both subsections, furthermore, the influence of deriving a wrong decision is analyzed. Therefore, at first, the optimal decisions for each scenario have to be determined. (see Section 3.4.1 and Figure 3.10) Afterward, the influence of choosing a wrong investment strategy can be measured. Therefore, the scenario optimal plant configurations are fixed and, combined with the other scenarios, the resulting objective values are calculated. The difference between the scenario optimal solution and the results of the non-optimal scenario plant design combinations demonstrates the influence of a wrong decision.

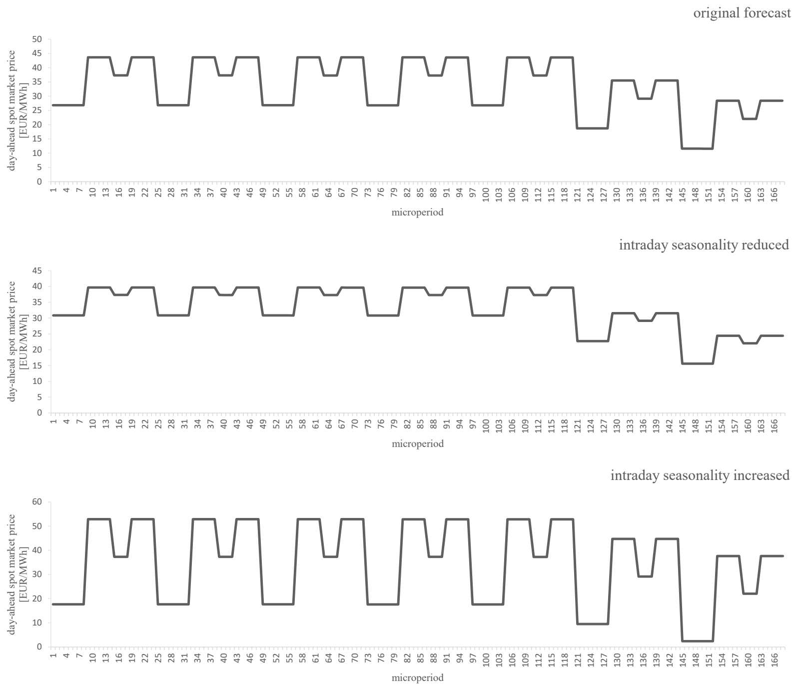

Figure 3.12: Price scenarios with different intraday seasonalities

3.5.3.1 Spot market price forecast

A numerical study is implemented in Python (2.7) to evaluate the optimization approach. The library Pandas is applied for data analysis. The solver Gurobi (7.5.1) is used together with the Pyomo (5.2) modeling tool interface. Experiments are run on a personal computer operated by Microsoft Windows 10 Professional, using an Intel CPU with 2.49 GHz and 8GB RAM.

First, the effect of the quality of the spot market price forecast is analyzed. As presented in Table 3.9 the base scenario builds a very accurate forecast because the objective value of the best case scenario with original spot market prices is almost similar to the base scenario. There is only a difference of 0.59 % between the NPV in the base scenario and the scenario with the original prices. If the forecasting error is increased by 90 % there is a difference in the objective values of almost 15 %. Accordingly, it is important to generate an accurate forecast.

Therefore, the component parts of the forecasting model should be separately analyzed.

The effects of the uncertainty within the specific components are depicted in Table 3.9 as well. It can be observed that a variation of the level component's forecast has no influence on the objective value. This is not surprising, because if the level of the spot market prices is higher or lower, the market premium, defined as the difference between the monthly average of the spot market prices and the EEG feed-in tariff, will be adversely lower or higher. Thus, the generated revenues at the spot market consisting out of spot market price and market premium will remain the same. The variation of the trend component $\hat{b}$ shows a rather small percentage effect on the objective value. However, an increase of 0.57 % (switched trend, see Section 3.5.3) of the NPV corresponds to additional 13,000 EUR for the biogas plant operator, which are often small farmers. Hence, even a small change can be relevant to them. The two scenarios regarding the intraday seasonality variation are leading to reverse effects. If the intraday seasonality is decreased, the objective value is decreased by more than 5 %. In contrast, if the intraday seasonality is increased, the objective value is increased by almost 8 %. Nevertheless, a variation of the intraday seasonality leads to a significant effect on the NPV of the investigated investment decision. The variation of the intraweek seasonality leads to a smaller effect than the intraday seasonality variation. However, the influence is still measurable, but a change within the intraweek seasonality is rather unrealistic as mentioned in Section 3.5.1. This is valid as well for the probability of a change in the intrayear seasonality. Even though, a reduction of the intrayear seasonality leads to a significant loss of NPV. An increase does not lead to a significant change because the potential biogas storages are too small to influence the long-term electricity production.

Table 3.9: Effect of forecast error, level, trend and seasonal components on the objective value

forecast error		level		trend		
red.	incr.	red.	incr.	red.	incr.	switch
-0.59 %	-14.66 %	0.00 %	0.00 %	0.23 %	-0.06 %	0.57 %

intraday		intraweek		intrayear	
red.	incr.	red.	incr.	red.	incr.
-5.56 %	7.83 %	-1.02 %	2.00 %	-5.56 %	0.02 %

variation in % compared to base scenario with NPV = 2,362,156 EUR

The effects of deriving a wrong decision are depicted in Table 3.10, based on a variation of the forecast error. Here, the scenario-optimal investment strategies j are calculated for each scenario. (see Section 3.4.1 and Figure 3.10) Thus, three scenario-optimal investment strategies are derived (2, 120, 128). For all of the three scenarios and all of the three investment strategies, the objective value is calculated and the percentage difference to the optimal solution NPV* is measured. It can be concluded that taking the wrong decision, based on an inaccurate price forecast, can lead to a significant loss of NPV. Especially, if the scenario-optimal decision and the made decision are extremely different like investment alternatives 2 and 120. To conclude, it is important to model all significant sources of uncertainty in the spot market prices within scenarios to find a robust solution, because an inaccurate forecast can lead to a significant loss of revenues for the biogas plant operator. The significant influences are the trend, the three seasonalities and the quality of the forecast in general.

Table 3.10: Effects of wrong decisions - forecast error

		forecast error	
j	base scenario	red.	inc.
120	-	-2.29 %	-7.11 %
128	-1.56 %	-	-7.17 %
2	-5.69 %	-1.59 %	-

variation in % compared to the scen. opt. alt.

3.5.3.2 Flexibility premium

Apart from the uncertain influences based on the spot market prices, the effect of the flexibility premium on the objective value is investigated. Therefore, the resulting NPV is compared using the best and worst case scenarios - granted and not granted flexibility premium. Compared to the optimal NPV* of the optimal investment strategy j = 120 of the base scenario, assuming to get the flexibility premium, a denial of this grant would lead to a tremendous loss of 88.72 %. Hence, the uncertainty within the flexibility premium determines the major influence on the investment decision compared to the other uncertainty sources.

Similar to the last subsection, effects of deriving a wrong decision are depicted in Table 3.11, based on granting or not granting of the flexibility premium. Therefore, the optimal decisions are derived for all of the previously mentioned price scenarios concerning the forecast error, level, trend, intraday, intraweek and intrayear seasonality combined with the best and worst case of the flexibility premium. Using these I = 26 scenarios, the following J' = 6 (see Figure 3.10) scenario optimal investment strategies can be derived: 2, 119, 120, 121, 126, 128. The values in Table 3.11 are generated using the base scenario for the spot market prices and the two scenarios of a granted or not granted flexibility premium. They show the variation in % of the objective value of a given investment strategy within the base scenario and an EEG-scenario, to the optimal objective value in this price-EEG-scenario combination. The base scenario optimal strategy with a granted flexibility premium is j = 120, resp. j = 2 if the flexibility premium is not granted. The results disclose that the investment decision depends strongly on the (un-) approval of the flexibility premium. If the flexibility premium is granted, typically an investment strategy with a large CHP plant extension and a large biogas storage is chosen. If not, only a small biogas storage should be built and no additionally CHP plant capacity should be installed. (investment strategy 2) Significant losses can be observed if the flexibility premium is granted and a non-optimal decision is derived. If the flexibility premium is not granted, the losses resulting out of non-optimal decisions are tremendous. For this reason, this analysis shows as well that the uncertainty within the flexibility premium determines the major influence on the investment decision.

Table 3.11: Effects of wrong decisions - flexibility premium

		deviation of NPV	
		granted flex. prem.	not granted flex. prem
j	2	-5.69 %	-
	119	-0.24 %	-85.34 %
	120	-	-85.02 %
	121	-0.01 %	-85.04 %
	126	-0.99 %	-86.34 %
	128	-1.56 %	-87.09 %

NPV*(base scen.; no grant) = NPV*(j = 2) = 1,778,597 EUR
NPV*(base scen.; grant) = NPV*(j = 120) = 2,362,156 EUR

3.5.4 Robust investment decision under uncertainty

After analyzing the sources of uncertainty and their effect on the optimal investment decision, the significant ones are used to derive a robust decision under uncertainty. As explained previously, the accuracy of the forecast as a whole, the trend and seasonal components and the uncertainty of the flexibility premium are identified as significant.

In order to reach the goal of giving decision support for the mentioned investment problem, the developed multi-stage approach, as depicted in Figure 3.10, is used to derive solutions. The first step, finding and building of sufficient price scenarios, is already finished. Thus, scenario optimal solutions can be generated using the identified significant scenarios and the developed SBPP model. Aforementioned, the significant sources of uncertainties lead to 11 scenarios, because the forecast accuracy is considered implicitly by varying the component parameters concerning trend and seasonality. Using those scenarios, the same six scenario optimal investment strategies as in the last subsection can be derived. For instance, the investment alternative 120 means that a gas storage with capacity 12,000 Nm^3 and additional electrical excess capacity with 5,500 kWh is installed. As the aim is to derive a robust solution concerning all scenarios, the solutions of all scenarios have to be compared. Hence, the determined solutions for the scenario-optimal investment strategies are fixed and the model is solved again for all scenarios and all six gathered plant designs. The results of these calculations are depicted in a solution matrix in Table 3.12.

Table 3.12: Scenario optimal results and evaluation using decision theory

		base scenario										
		gran.	not gran.		trend		intraday		intraweek		intrayear	
		flex. pr.	flex. pr.	red.	inc.	switch	red.	inc.	red.	inc.	red.	inc.
j	2	30.11	3.88	30.34	29.93	30.89	27.11	30.11	29.35	31.44	30.10	30.13
	119	37.63	-84.78	37.98	37.57	38.42	30.05	37.63	36.59	39.87	37.63	37.65
	120	37.96	-84.44	38.28	37.87	38.75	30.29	37.96	36.56	40.72	37.96	37.98
	121	37.94	-84.46	38.23	37.83	38.73	30.18	37.94	36.00	41.44	37.95	37.97
	126	36.60	-85.81	36.74	36.35	37.39	28.61	36.60	32.74	43.08	36.62	36.62
	128	35.81	-86.59	35.93	35.56	36.61	27.80	35.81	31.81	42.63	35.83	35.83

		flex. premium not granted			flex. premium granted		
		Maximin	Hurwicz		Maximin	Hurwicz	
			$\lambda = 0.2$	$\lambda = 0.4$		$\lambda = 0.2$	$\lambda = 0.4$
j	2	3.88	9.39	17.66	27.11	27.97	29.28
	119	-84.78	-59.85	-22.45	30.05	32.02	34.96
	120	-84.44	-59.41	-21.86	30.29	32.37	35.51
	121	-84.46	-59.28	-21.51	30.18	32.44	35.81
	126	-85.81	-60.03	-21.36	28.61	31.50	35.84
	128	-86.59	-60.75	-21.98	27.80	30.77	35.22

deviation in % to EEG feed-in tariff within the planning horizon ($1,712,173$ EUR)

Within Table 3.12 the percentage deviation of the objective values, depending on the optimized operational biogas plant schedule, the chosen investment strategy and the covered scenario, to the guaranteed EEG feed-in tariff within the planning horizon is depicted. The EEG feed-in tariff represents the unadapted state of the biogas plant, previous to a potential investment decision and thus the conventional plant design without an investment and without direct marketing. Hence, this case is used as a reference strategy in order to normalize the objective values in the solution matrix. The objective value of this reference strategy is $1,712,173$ EUR, thus this strategy is profitable. The given values in Table 3.12 demonstrate the deviations of the objective values considering a specific investment strategy and scenario to the reference strategy in percent. For instance, the value of 30.11 for the investment strategy 2 considering the scenario with a granted flexibility premium and the base scenario forecast means that the resulting objective value is 30.11% higher as the reference strategy. Hence, additional revenues would be generated. A negative value means that in the specific case fewer revenues are generated than with the reference strategy. Accordingly, an investment and using of direct marketing would not be beneficial compared to the base scenario. However, the objective values of all investigated strategy-scenario combinations are positive, as there are no resulting changes smaller than -100%, which would lead to a negative NPV. For this reason, each of the investment strategies itself is evaluated as beneficial because of the positive NPV. However, if the investment strategies are compared to the reference strategy, the investment alternatives 119, 120, 121, 126 and 128 should not be chosen if the flexibility premium is not granted, because the NPV of the investment strategy is lower as in the reference scenario. Apart from the optimal choices of investment strategies, the results of the numerical experiment show that in every scenario in which the flexibility premium is possible the premium is requested. The influence of the flexibility premium on the results is demonstrated as well in Table 3.12. As given in the table, the objective values are always higher if the premium is granted than otherwise. Additionally, each of the six investigated investment strategies is beneficial compared to the reference strategy if the flexibility premium is granted. If not, high investments (119, 120, 121, 126, 128) are generally not beneficial compared to the reference scenario.

In the last step of the developed multi-stage approach, a robust solution for a risk averse decision maker is derived. Thus, the rules of decision theory are applied to the results in the solution matrix. Since the generated scenarios are not rated with probabilities, a decision under uncertainty is necessary. Therefore, several decision rules can be applied. However, as Scholl (2001) has revealed in an overview regarding decision theory, only the Maximin rule and the Hurwicz's decision rule lead to great solution robustness. (Scholl (2001), Chap. 4) With the Maximin rule, only the worst scenario for every action (i.e., strategy) is considered. After that, the action is chosen which is best among the worst. Hence, this decision rule represents a strong risk aversion of a very pessimistic decision maker, always expecting the worst, but trying to make the best decision given this assumption. (Scholl, 2001) As depicted in Table 3.12 the decision tremendously depends on the granting of the flexibility premium. If the flexibility premium is not granted, the investment strategy 2 is chosen. (no CHP plant extension, 5000 Nm^3 biogas storage) If the flexibility premium is granted, the investment alternative 120 should be chosen. (5.500 kWh CHP plant extension, 12000 Nm^3 biogas storage)

As well as the application of the Maximin rule, the adaption of the decision rule of Hurwicz leads to high solution robustness for a risk-averse decision maker. Therefore, a small risk parameter $0 \leq \lambda \leq 1$ has to be assumed. λ can be interpreted as follows: $\lambda = 0$ shows a strong risk aversion (same result as Maximin rule) whereas $\lambda = 1$ means that the decision maker has no aversion against risk. (Scholl, 2001),(Hurwicz, 1951) As the aim is to model a risk-averse decision maker, values of $\lambda = 0.2$ and $\lambda = 0.4$ are assumed. Using the decision rule of Hurwicz, a linear combination of the risk parameter λ and the worst, as well as the best scenario solution, is maximized. This leads to the following calculation of the Hurwicz-criterion:

$$\Phi(j) = (1-\lambda) \cdot min\left\{NPV_{ji}|i = 1,...,I\right\} + \lambda \cdot max\left\{NPV_{ji}|i = 1,...,I\right\} \tag{3.18}$$

Here j represents the different possible actions of the decision maker (investment strategies), i represents the considered scenarios and NPV_{ji} is defined as the objective value in scenario i with strategy j. (Hurwicz, 1951) The application of the Hurwicz criterion leads to the same results as the Maximin rule, if the flexibility premium is not granted. If the flexibility premium is granted, the optimal decisions using the Maximin rule and the Hurwicz criterion with $\lambda = 0.2$ and $\lambda = 0.4$ are slightly different. However, all of the chosen optimal decisions have in common that the same CHP plant extension of 5.500 kWh is installed. Only the size of the biogas storage is slightly different. As mentioned, an increasing parameter λ represents a decreasing aversion against risk. Accordingly, with decreasing risk aversion a slightly larger biogas storage should be built.

Summarizing the previous results, it should be noted that the decision of the risk averse decision maker depends heavily on the (un-) certainty of the flexibility premium. If the flexibility premium is truly uncertain, the optimal decision would be a minor adjustment of the biogas plant design. If there are realistic chances that the flexibility premium is granted, a high investment using alternatives 120, 121 or 126 would be optimal. Thus, the influence of this subsidy on the decision is tremendous and the decision maker should try to get better information on the chances that his request for the flexibility premium would receive a positive answer. The developed approach can help to show such influences and gives an idea of the resulting consequences.

3.6 Summary and outlook

In this paper, it was examined how biogas plants operated flexibly can help to balance volatility carbon-neutrally and without using nuclear resources within the power grid, if the shares of renewable resources are increased. In order to operate biogas plants flexibly, adjustments of the biogas plant configurations are necessary, which cause investments. Thus, it is investigated how the technical biogas plant design can be modified to increase the flexibility and reach a demand oriented power generation. The generated power should afterward be sold through direct marketing at the power exchange EPEX Spot SE. Hence, the potential revenues at the spot market are characterized by uncertainty. In order to support this strategic, long-term investment decision and generate a robust solution for a risk-averse decision maker, a novel multi-stage approach considering uncertain revenues is presented. The heart of the approach is a novel deterministic MILP model to support the investment decision (SBPP), consisting out of investment decisions concerning biogas storages and additional CHP plant capacities, named investment strategies. However, as the spot market prices are varying dynamically over time these variations, or stochasticity, are considered by simulating several spot market price forecasts using times series decomposition and thus using a deterministic optimization model in an uncertain environment. Therefore, the significant sources of uncertainties were identified and analyzed. The spot market price forecasts are then used to optimize an operational plant schedule. The resulting payments and payouts within the operational plant schedule are used to evaluate the investment strategies.

The numerical experiments reveal that the investment decision depends not only on the development of the spot market prices but also on the governmental subsidies, namely the flexibility and market premium. In terms of the forecast of spot market prices, it is identified that the forecast accuracy is crucial for the success of an investment strategy. In order to model relevant market developments in the future, it was discovered that it is necessary to model trend and seasonal characteristics of the spot market prices. The uncertainty of the flexibility premium determines the choice of doing an investment or not as well. If the flexibility premium is granted, a high investment is chosen in any case of spot market price developments. If not, a small investment is chosen. To conclude, the developed approach gives decision support to a risk-averse biogas plant operator who decides about choosing direct marketing, producing electricity demand-driven and therefore an adjustment of the biogas plant design. All governmental requirements and regulations of the German energy market are modeled and the possible sources of revenues are distinguished. As well, the resulting payouts are considered. Hence, the long-term investment decision can be supported by optimizing an operational schedule.

Nevertheless, there is potential for further research. As explained in Section 3.5, the probabilities of the distinguished scenarios should be considered to derive a more detailed solution. In the future, these probabilities could be covered more precisely within the optimization model by applying stochastic variables using probability distributions for market prices and subsidies. Accordingly, all scenarios and all investment alternatives could be considered simultaneously to derive an optimal solution directly. However, this would lead to a stochastic optimization model. In general, more effort in terms of computation time is necessary to derive an optimal solution for a stochastic model than for a deterministic one.

The decision framework in this paper is characterized by several assumptions. One of these assumptions is the steady gas production rate within the digester. Hence, the resulting biogas plant after the investment is a type II plant. The analysis of the impact of a flexible biogas production rate on the investment decision and thus a type III biogas plant can help to make the developed approach more applicable in practice. With a slightly flexible biogas production, it could be possible to compensate for monthly intrayear fluctuations of the prices. Additionally, it is assumed that only pre-defined combinations of single biogas storages and single CHP plant capacity extensions can be chosen. A future model could consider the possibility to combine different CHP plants or biogas storages more flexibly .

Apart from the mentioned extensions, other extensions could cover the risk attitude of the decision maker using the Conditional Value at Risk, the robustness of the solution using a robustness function, several energy markets apart from the day-ahead market and the marketing of the produced heat as a second product. Moreover, in this paper, the biogas plant is examined independently from other power plants, power storages or power consumers. It could be beneficial to examine the biogas plant design within a network of other market participants in the future. One possible concept to model a biogas plant within the network is to assume the biogas plant as part of a virtual power plant. Here, other flexibility options, for instance, pumped-storage power plants, are considered besides the biogas plant, which can lead to other design decisions.

Bibliography

Agora Energiewende, 2018. Aktuelle Stromdaten/Agorameter. URL: https://www.agora-energiewende.de/service/aktuelle-stromdatenagorameter/chart/power_generation/06.08.2018/09.08.2018/. accessed 2018-08-09.

Balussou, D., Heffels, T., McKenna, R., Möst, D., Fichtner, W., 2014. An Evaluation of Optimal Biogas Plant Configurations in Germany. Waste and Biomass Valorization 5, 743–758. doi:10.1007/s12649-013-9284-1.

BDEW Bundesverband der Energie- und Wasserwirtschaft e.V., 2018. Monatlicher Stromverbrauch in Deutschland. URL: https://www.bdew.de/media/documents/Stromverbrauch-Vgl-Vorjahresmonat_online_o_monatlich_Ki_14052018.pdf. accessed 2018-08-09.

Belsnes, M.M., Wolfgang, O., Follestad, T., Aasgård, E.K., 2016. Applying successive linear programming for stochastic short-term hydropower optimization. Electric Power Systems Research 130, 167–180. doi:10.1016/j.epsr.2015.08.020.

Beraldi, P., Conforti, D., Violi, A., 2008. A two-stage stochastic programming model for electric energy producers. Computers & Operations Research 35, 3360–3370. doi:10.1016/j.cor.2007.03.008.

BiomassV, 2016. Verordnung über die Erzeugung von Strom aus Biomasse (Biomasseverordnung - BiomasseV).

Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., Yang, M., 2007. Investment risks under uncertain climate change policy. Energy Policy 35, 5766–5773. doi:10.1016/j.enpol.2007.05.030.

Bundesnetzagentur. Beschlusskammer 6, 2011a. BK6-10-097. URL: https://www.bundesnetzagentur.de/DE/Service-Funktionen/Beschlusskammern/1BK-Geschaeftszeichen-Datenbank/BK6-GZ/2010/2010_0001bis0999/2010_001bis099/BK6-10-097bis-099/BK6-10-097_Beschluss_2011_04_12.pdf;jsessionid=D4FDC022442CF0FDFF8547C4C727508C?__blob=publicationFile&v=3. accessed 2018-07-05.

Bundesnetzagentur. Beschlusskammer 6, 2011b. BK6-10-098. URL: https://www.bundesnetzagentur.de/DE/Service-Funktionen/Beschlusskammern/1BK-Geschaeftszeichen-Datenbank/BK6-GZ/2010/2010_0001bis0999/2010_001bis099/BK6-10-097bis-099/BK6-10-098_Beschluss_2011_04_12.pdf?__blob=publicationFile&v=2. accessed 2018-07-05.

Bundesnetzagentur. Beschlusskammer 6, 2011c. BK6-10-099. URL: https://www.bundesnetzagentur.de/DE/Service-Funktionen/Beschlusskammern/1BK-Geschaeftszeichen-Datenbank/BK6-GZ/2010/2010_0001bis0999/2010_001bis099/BK6-10-097bis-099/BK6-10-099_Beschluss_2011_10_18.pdf?__blob=publicationFile&v=2. accessed 2018-07-05.

Bundestag, 2011. Gesetz zur Neuregelung des Rechtsrahmens für die Förderung der Stromerzeugung aus erneuerbaren Energien.

Chazarra, M., García-González, J., Pérez-Díaz, J.I., Arteseros, M., 2016. Stochastic optimization model for the weekly scheduling of a hydropower system in day-ahead and secondary regulation reserve markets. Electric Power Systems Research 130, 67–77. doi:10.1016/j.epsr.2015.08.014.

Deutsche Bundesbank, 2017. Abzinsungszinssätze gemäß § 253 Abs. 2 HGB / 7 Jahresdurchschnitt. URL: https://www.bundesbank.de/Redaktion/DE/Downloads/Statistiken/Geld_Und_Kapitalmaerkte/Zinssaetze_Renditen/abzinsungszinssaetze.pdf;jsessionid=0000GZtDCJRS0sdfohAZEF49ywT:-1?__blob=publicationFile. accessed 2018-07-05.

EEG, 2000. Gesetz für den Vorrang erneuerbarer Energien, Erneuerbare-Energien-Gesetz 2000. EEG, vom BGBl. I 2003 S. 3074.

EEG, 2012. Gesetz für den Ausbau erneuerbarer Energien, Erneuerbare-Energien-Gesetz 2012. EEG, vom BGBl. I S. 1754.

EEG, 2014. Gesetz für den Ausbau erneuerbarer Energien, Erneuerbare-Energien-Gesetz 2014. EEG, vom BGBI. I S. 1218.

EEG, 2017. Gesetz für den Ausbau erneuerbarer Energien, Erneuerbare-Energien-Gesetz 2017. EEG, vom BGBl. I S. 3106.

EPEX Spot, 2018. Marktdaten Day-Ahead-Auktion. URL: https://www.epexspot.com/de/marktdaten/dayaheadauktion. accessed 2018-08-07.

Fichtner, S., Meyr, H., 2017. Strategic Supply Chain Planning in Biomass-Based Industries: A Literature Review of Quantitative Models, in: Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), Knowledge-driven developments in the bioeconomy. Springer Verlag, Cham. Economic complexity and evolution, pp. 259–291.

Fichtner, S., Meyr, H., 2019. Biogas plant optimization by increasing its flexibility considering uncertain revenues. Hohenheim Discussion Papers in Business, Economics and Social Sciences 07, 1–48. Stuttgart.

Fleischmann, B., Koberstein, A., 2015. Strategic Network Design, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 107–123. doi:10.1007/978-3-642-55309-7_6.

Fleischmann, B., Meyr, H., Wagner, M., 2015. Advanced planning, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 71–95. doi:10.1007/978-3-642-55309-7_4.

Fleten, S.E., Kristoffersen, T.K., 2008. Short-term hydropower production planning by stochastic programming. Computers & Operations Research 35, 2656–2671. doi:10.1016/j.cor.2006.12.022.

FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2013. Biogas.

FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2017. Faustzahlen. URL: https://biogas.fnr.de/daten-und-fakten/faustzahlen/. accessed 2017-11-07.

Fraunhofer ISE, 2018a. Stromimport und -export von Deutschland in Woche 32 2018. URL: https://www.energy-charts.de/power_de.htm?source=import-export&year=2018&week=32. accessed 2018-08-09.

Fraunhofer ISE, 2018b. Stromproduktion in Deutschland in Woche 32 2018. URL: https://www.energy-charts.de/power_de.htm?source=all-sources&year=2018&week=32. accessed 2018-08-13.

García-González, J., Parrilla, E., Mateo, A., 2007. Risk-averse profit-based optimal scheduling of a hydro-chain in the day-ahead electricity market. European Journal of Operational Research 181, 1354–1369. doi:10.1016/j.ejor.2005.11.047.

Gohsen, D., Allelein, H.J., 2015. Development of a Market-based Optimisation Model for a Demand-based and Storable Electricity Production from Biogas. Energy Procedia 73, 79–86. doi:10.1016/j.egypro.2015.07.565.

Haghi, H.V., Tafreshi, S., 2007. An Overview and Verification of Electricity Price Forecasting Models. IEEE Xplore, [Piscataway, N.J.].

Hahn, H., Ganagin, W., Hartmann, K., Wachendorf, M., 2014a. Cost analysis of concepts for a demand oriented biogas supply for flexible power generation. Bioresource technology 170, 211–220. doi:10.1016/j.biortech.2014.07.085.

Hahn, H., Hartmann, K., Bühle, L., Wachendorf, M., 2015. Comparative life cycle assessment of biogas plant configurations for a demand oriented biogas supply for flexible power generation. Bioresource technology 179, 348–358. doi:10.1016/j.biortech.2014.12.007.

Hahn, H., Krautkremer, B., Hartmann, K., Wachendorf, M., 2014b. Review of concepts for a demand-driven biogas supply for flexible power generation. Renewable and Sustainable Energy Reviews 29, 383–393. doi:10.1016/j.rser.2013.08.085.

Heffels, T., McKenna, R., Fichtner, W., 2012. Direct marketing of electricity from biogas and biomethane: An economic analysis of several business models in Germany. Journal of Management Control 23, 53–70. doi:10.1007/s00187-012-0153-z.

Hochloff, P., Braun, M., 2014. Optimizing biogas plants with excess power unit and storage capacity in electricity and control reserve markets. Biomass and Bioenergy 65, 125–135. doi:10.1016/j.biombioe.2013.12.012.

Hübner, R., 2007. Strategic Supply Chain Management in Process Industries: An Application to Specialty Chemicals Production Network Design. volume 594. Springer, Berlin, Heidelberg.

Hurwicz, L., 1951. The Generalised Bayes Minimax Principle: A Criterion for Decision Making under Uncertainty. Cowles Commission Discussion Paper 355, 1–7.

Hüttner, M., 1986. Prognoseverfahren und ihre Anwendung. De Gruyter, Berlin.

Ju, L., Tan, Z., Yuan, J., Tan, Q., Li, H., Dong, F., 2016. A bi-level stochastic scheduling optimization model for a virtual power plant connected to a wind–photovoltaic–energy storage system considering the uncertainty and demand response. Applied Energy 171, 184–199. doi:10.1016/j.apenergy.2016.03.020.

Keles, D., Genoese, M., Möst, D., Fichtner, W., 2012. Comparison of extended mean-reversion and time series models for electricity spot price simulation considering negative prices. Energy Economics 34, 1012–1032. doi:10.1016/j.eneco.2011.08.012.

Keles, D., Möst, D., Fichtner, W., 2011. The development of the German energy market until 2030—A critical survey of selected scenarios. Energy Policy 39, 812–825. doi:10.1016/j.enpol.2010.10.055.

Keles, D., Scelle, J., Paraschiv, F., Fichtner, W., 2016. Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks. Applied Energy 162, 218–230. doi:10.1016/j.apenergy.2015.09.087.

Kumbaroğlu, G., Madlener, R., Demirel, M., 2008. A real options evaluation model for the diffusion prospects of new renewable power generation technologies. Energy Economics 30, 1882–1908. doi:10.1016/j.eneco.2006.10.009.

Lehnert, W., Rehfeldt, K., Diekmann, J., Hofmann, L., 2011. Flexible Stromproduktion aus Biogas und Biomethan: Die Einführung einer Kapazitätskomponente als Förderinstrument: Bericht zum Projekt - Weiterentwicklung und wissenschaftliche Begleitung der Umsetzung des Integrations-Bonus nach § 64 Abs. 1.6 EEG.

Makridakis, S.G., Wheelwright, S.C., Hyndman, R.J., 2010. Forecasting: Methods and applications. 3 ed., Wiley, New York.

Meyr, H., Wagner, M., Rohde, J., 2015. Structure of Advanced Planning Systems, in: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. 5 ed.. Springer, Berlin, Heidelberg. Springer Texts in Business and Economics, pp. 99–106. doi:10.1007/978-3-642-55309-7_5.

Möst, D., Keles, D., 2010. A survey of stochastic modelling approaches for liberalised electricity markets. European Journal of Operational Research 207, 543–556. doi:10.1016/j.ejor.2009.11.007.

Nojavan, S., Zare, K., 2013. Risk-based optimal bidding strategy of generation company in day-ahead electricity market using information gap decision theory. International Journal of Electrical Power & Energy Systems 48, 83–92. doi:10.1016/j.ijepes.2012.11.028.

Nosratabadi, S.M., Hooshmand, R.A., Gholipour, E., 2017. A comprehensive review on microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems. Renewable and Sustainable Energy Reviews 67, 341–363. doi:10.1016/j.rser.2016.09.025.

Pandžić, H., Morales, J.M., Conejo, A.J., Kuzle, I., 2013. Offering model for a virtual power plant based on stochastic programming. Applied Energy 105, 282–292. doi:10.1016/j.apenergy.2012.12.077.

Peik-Herfeh, M., Seifi, H., Sheikh-El-Eslami, M.K., 2013. Decision making of a virtual power plant under uncertainties for bidding in a day-ahead market using point estimate method. International Journal of Electrical Power & Energy Systems 44, 88–98. doi:10.1016/j.ijepes.2012.07.016.

Schlesinger, M., Lindenberger, D., Lutz, C., 2014. Entwicklung der Energiemärkte - Energiereferenzprognose: Projekt Nr. 57/12 des Bundesministeriums für Wirtschaft und Technologie, Berlin.

Scholl, A., 2001. Robuste Planung und Optimierung: Grundlagen - Konzepte und Methoden - experimentelle Untersuchungen ; mit 105 Tabellen. Physica-Verl., Heidelberg.

Singh, V.K., Singal, S.K., 2017. Operation of hydro power plants-a review. Renewable and Sustainable Energy Reviews 69, 610–619. doi:10.1016/j.rser.2016.11.169.

Statistisches Bundesamt, 2017. Preise: Daten zur Energiepreisentwicklung: Lange Reihen von Januar 2000 bis August 2017. URL: https://www.destatis.de/DE/Publikationen/Thematisch/Preise/Energiepreise/EnergiepreisentwicklungPDF_5619001.pdf?__blob=publicationFile. accessed 2018-08-07.

Tajeddini, M.A., Rahimi-Kian, A., Soroudi, A., 2014. Risk averse optimal operation of a virtual power plant using two stage stochastic programming. Energy 73, 958–967. doi:10.1016/j.energy.2014.06.110.

Weron, R., 2006. Modeling and forecasting electricity loads and prices: A statistical approach. Wiley finance series, John Wiley et Sons, Chichester, England.

Wichmann, M.G., Johannes, C., Spengler, T.S., 2018. An extension of the general lot-sizing and scheduling problem (GLSP) with time-dependent energy prices. Journal of Business Economics 89, 481–514. doi:10.1007/s11573-018-0921-9.

Yang, M., Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., 2008. Evaluating the power investment options with uncertainty in climate policy. Energy Economics 30, 1933–1950. doi:10.1016/j.eneco.2007.06.004.

Zamani, A.G., Zakariazadeh, A., Jadid, S., Kazemi, A., 2016. Stochastic operational scheduling of distributed energy resources in a large scale virtual power plant. International Journal of Electrical Power & Energy Systems 82, 608–620. doi:10.1016/j.ijepes.2016.04.024.

Ziel, F., Steinert, R., 2016. Electricity price forecasting using sale and purchase curves: The X-Model. Energy Economics 59, 435–454. doi:10.1016/j.eneco.2016.08.008.

Ziel, F., Steinert, R., Husmann, S., 2015. Efficient modeling and forecasting of electricity spot prices. Energy Economics 47, 98–111. doi:10.1016/j.eneco.2014.10.012.

4 Operational and strategic optimization of biogas plants based on variable substrate feeding

Abstract[4] The share of electricity produced from renewable energy is constantly increasing in Germany and worldwide to reach ambitious climate policy targets. In addition to the use of wind and solar energy, the energetic use of biomass is a promising carbon-neutral alternative for the future. Furthermore, energy from biomass can be used as a balancing power to compensate power supply from fluctuating sources, such as solar or wind, if the biogas plant design is adjusted adequately. In order to achieve a flexibly schedulable biogas plant, the design of this plant has to be adjusted to decouple the biogas and electricity production. Therefore, biogas storage possibilities and additional electrical capacity are necessary. Additionally, the biogas production rate may be influenced operationally by variable substrate feeding. This research addresses the strategic and operational decisions to increase the flexibility of a biogas plant by installing biogas storages and additional electrical capacities under consideration of revenues out of direct marketing on the energy spot market. In order to support these decisions, an operative plant schedule for the future, considering (non-) linear technical characteristics and the legal framework is optimized. Therefore, mixed-integer linear programming (MILP) models with integrated approximation approaches of non-linear parts are constructed. Furthermore, the influences of fluctuating spot market prices, governmental subsidies, and biomass feedstock prices on the decisions are analyzed for a fictional case example, which is based on a biogas plant in southern Germany. These numerical experiments show that variable substrate feeding can play a decisive role during the optimization of a biogas plant schedule as part of a long-term design optimization. However, the size of the strategic optimization problem makes the use of a heuristic solution algorithm necessary.

Keywords Variable substrate feeding, Piecewise linear approximation, Rieman sums

4.1 Introduction

At the United Nations Climate Change Conference 2015 in Paris, ambitious climate policy targets have once again been defined. In order to reach these targets, a mixture of actions has to be identified to push the utilization of renewable energy resources and reduce carbon emissions. In addition to the use of wind and solar energy, the energetic use of biomass is a promising carbon-neutral alternative for the future. In contrast to wind and solar energy, which are characterized by a highly volatile and only partly controllable production, biomass can be used to produce energy flexibly and demand-oriented. Hence, energy, produced demand-oriented using biogas plants, can be used to balance the volatile energy production out of wind and solar energy. In Germany, for instance, the shares of wind and solar within the energy mix are very high. Thus, the great potential of other flexible resources is necessary to balance these shares.

As mentioned, energy production based on biomass in biogas plants can be one of several alternatives to stabilize energy production. If energy is produced out of biomass, the competition with other biomass utilization pathways has to be considered, because biomass is a scarce resource. (Fichtner and Meyr, 2017) Nevertheless, the potential

[4] This paper has been written by Stephan Fichtner (Department of Supply Chain Management, University of Hohenheim, Stuttgart).

of biomass, for example in the form of residues, to reach a renewable energy production is significant. (Scarlat et al., 2018)

In order to use this potential, it is necessary to run the existing biogas plants demand-oriented and flexibly. As Fichtner and Meyr (2019) have shown, it is required in many cases to modify the biogas plant configuration first, before a flexible energy production is possible. As depicted in Figure 4.1 the most predominant configuration of biogas plants, located in Germany, is completely inflexible, as biomass is transformed into biogas using digestion processes and this biogas is further burned in combined heat and power (CHP) plants to produce electricity and heat with stable production rates. Hence, an adjustment of the configuration has to be made, as shown in Figure 4.2. Fichtner and Meyr (2019) distinguish three possible flexible plant configurations, which can be reached. Within the first configuration the biogas is upgraded and injected into the natural gas grid to decouple biogas and electricity production. In the second configuration the two production processes are decoupled by a biogas storage. The third configuration is an extension of the second one, in which the biogas production is flexibilized as well. What all those configurations have in common is that investments are needed to adjust the conventional biogas plants. These investments should then be amortized via revenues on the energy market. The major issue in this investment-planning problem is that future revenues on the energy market are depending on market development and are consequently uncertain. To deal with this uncertainty is a major part of the study by Fichtner and Meyr (2019). During their work, they developed an optimization approach, which is used to optimize the plant configuration based on future market earnings. The uncertainty of these earnings is considered using scenarios. The objective of Fichtner and Meyr (2019) is to reach a type II biogas plant, as depicted in Figure 4.2.

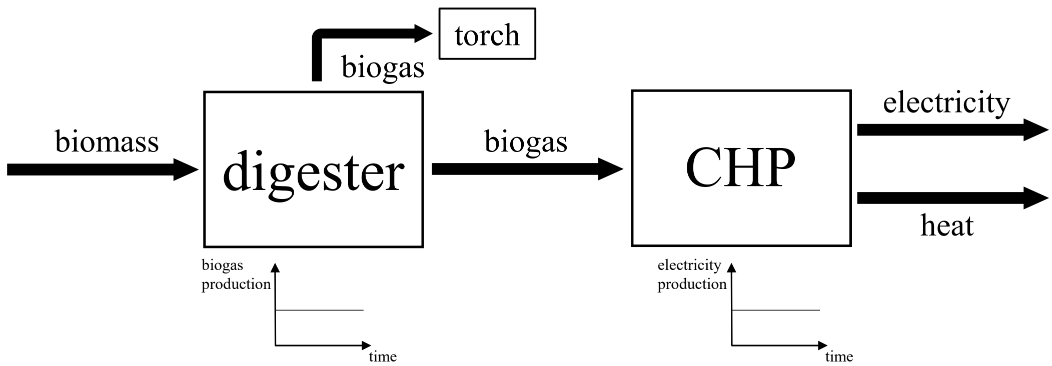

Figure 4.1: Conventional biogas plant configuration (see Fichtner and Meyr (2019))

Within this paper, the approach of Fichtner and Meyr (2019) is extended. The mentioned approach is characterized by a multi-stage optimization procedure. In a first step, the operational biogas schedule is optimized to calculate potential future earnings. These potential earnings have to be used later on to evaluate several biogas plant configurations with respective investments. Thus, the optimization of the operational biogas plant schedule is a crucial element of the strategic planning problem. The major part of this study is to include the process of variable substrate feeding and the resulting volatile biogas production rate into the mentioned operational schedule. Thus, a type III instead of a type II plant is considered. Variable substrate feeding means that the flow of biomass into the digester is flexibilized. Thus, the inflow and as a consequence the biogas production processes are mutable. The focus of this work is on the implementation of variable biogas production rates in the OBPP (operational biogas plant problem) model of Fichtner and Meyr (2019) and the evaluation of resulting economic effects. In a second step, the conclusions regarding the consideration of variable substrate feeding in the optimized operational schedule can be used for the strategic optimization. On the basis of the mainly bio-chemically or technically oriented existing literature regarding variable substrate feeding, the extension is considered to be beneficial, because the realization of such a flexible biogas production can reduce the necessary biogas storage capacities and thus the related investments.

The remainder of this paper is organized as follows: In Section 4.2, a technical overview of biogas production using variable substrate feeding is given. Subsequently in Section 4.3 relevant literature is analyzed. Within Section 4.4 the OBPP and SBPP (strategic biogas plant problem) models by Fichtner and Meyr (2019) are extended and approximation approaches regarding non-linear biogas production rates are introduced. The extended models are then tested using numerical experiments in Section 4.5. Finally, Section 4.6 summarizes the results and identifies opportunities for further extensions or general future research.

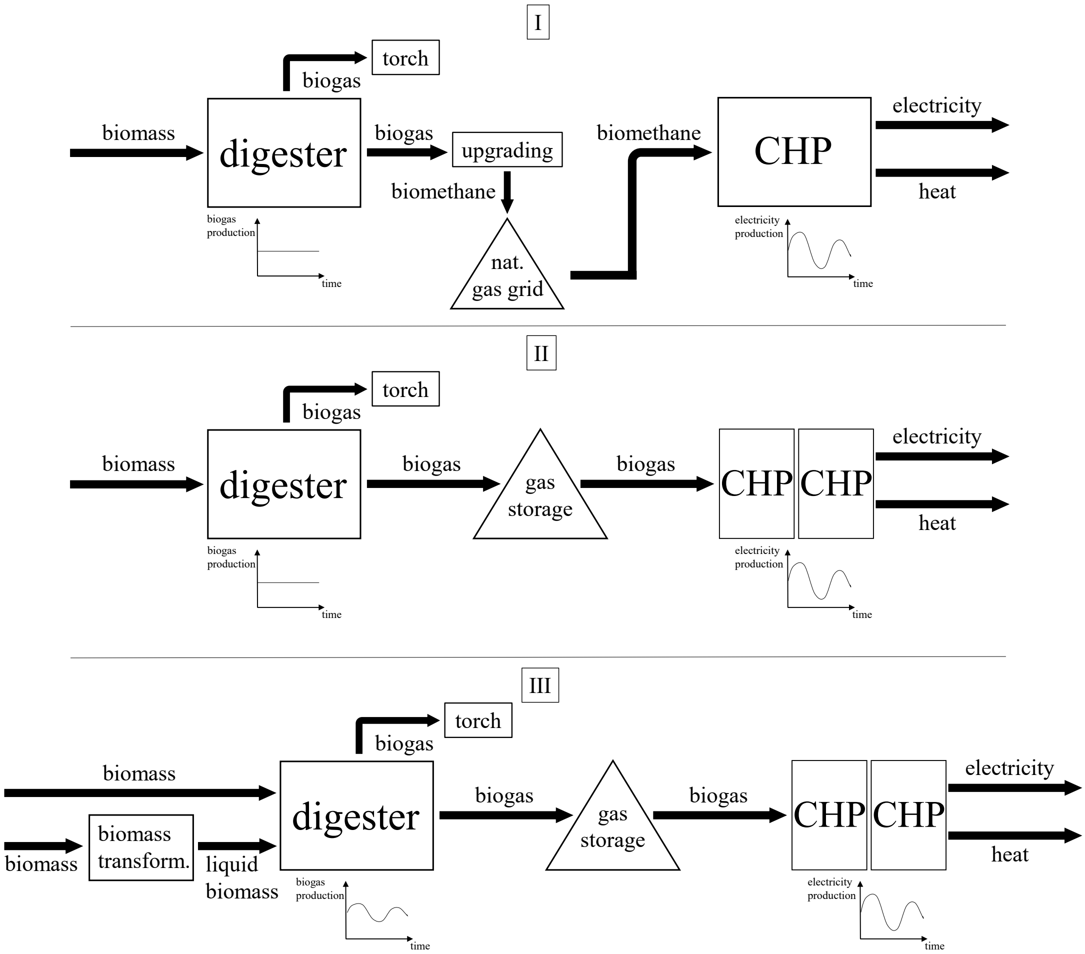

Figure 4.2: Further biogas plant configurations (see Fichtner and Meyr (2019))

4.2 Variable substrate feeding in biogas plants

In Section 4.2 an overview of variable substrate feeding in biogas plants, in particular an overview of the biogas plant functionality and the challenges and opportunities in the German energy market, is given.

4.2.1 Biogas plant functionality

Aforementioned in Section 4.1, several biogas plant configurations can be distinguished. These configurations are depicted in Figures 4.1 and 4.2. As mentioned, the conventional biogas plant design is characterized by great inflexibility. In this conventional case, biomass as a substrate is used to produce biogas through a combustion process in a digester. Afterward, the produced biogas is directly burned in a CHP plant to produce electricity and the by-product heat. The biogas production within the digester is continuous. If the biogas production rate is greater than the available biogas capacity in the storage plus the amount burned in the CHP, the excess gas has to be burned using a torch.

The ability for demand-oriented electricity production is according to Mauky et al. (2015) dependent on several factors. Several characteristics, which can be adjusted, are the type and capacity of biogas usage, the gas storage capacity on-site, the type of conversion process, and the substrate feeding management. The applications of these possible adjustments end up in the flexible biogas plant configurations, which are shown in Figure 4.2. It is either possible to upgrade the produced biogas to biomethane, inject it into the natural gas grid and use the grid as a gas storage (type I), decouple biogas and electricity production by installing biogas storage and additional electrical capacity (type II) or to decouple biogas and electricity production and additionally flexibilize the biogas production itself (type III). (Fichtner and Meyr, 2019) As explained in Section 4.1, the objective of this paper is to investigate the adjustment of a conventional biogas plant into a type III plant.

The important difference between a type II and a type III biogas plant is the flexibility of the biogas production process. Here, greater flexibility of the digester can be achieved by an adequate variable substrate feeding management related to the degradation kinetics of the used substrates. (Ahmed and Kazda, 2017) Traditionally, biogas plants are operated with a continuous feed and constant feedstock mixture. Thus, the biogas is produced with a constant rate and high efficiency. (Ertem et al., 2016) If the biogas production process should be influenced, this can be achieved by a variation of the substrate-feeding interval, the substrate type, and the feeding quantity. Hence, the biogas production can follow a demand pattern. The digestion times of different substrates vary from several hours up to several days. In order to increase the biogas production rate, easily degradable substrates can be used. A pre-conversion of the used substrate through a biomass transformation from solid into liquid biomass can help to speed up the digestion processes but is not necessary. (Hahn et al., 2014) Studies published by Mauky et al. (2017) and others show that the biogas production rate increases after a feeding event until a production peak is reached, afterward the biogas production rate decreases rapidly before it turns into a stable decrease. (see Figure 4.3) The time until the peak is reached and the amplitude of the effect depend on the specific biomass feedstock. If a biogas plant operator pursues the goal of increasing the biogas production rate for a permanent period of time, the frequency of the feeding events should be increased. Nevertheless, the maximum production of the digester is limited because if the digester is permanently fed with new substrate, which means that the time between substrate feedings is nearly zero, the maximum production is reached. Several biomass feedstocks can be used simultaneously in co-digestion. The biogas production rate in total is not influenced by the mixture of the co-digested substrates. In contrast, the specific biogas production rates per feedstock can be linearly summed up. (Ertem et al., 2016)

Aforementioned, the effect of variable substrate feeding is realized during the digestion process in the digester. This digester is typically characterized by its size, and the used technology, for instance, in terms of the used agitator, mixing or feeding systems. The digestion process is depicted in Figure 4.4 as an input-output-process. Used inputs are one or several biomass feedstock types, measured in kg and m^3, the usage of the digester as a production factor in time units (TU) and microorganisms in pieces (pc), which control the digestion processes. This biomass is feed into the digester, which is due to its size characterized by a capacity, which is typically measured in m^3. The feeding process is hard-constrained by the capacity, because with every feeding event the amount of fed substrate is automatically obtained using a spillover. Thus, the filling level within the digester is constant in a steady-state system. Outputs of the process are biogas, measured in Nm^3 and digestion residuals in liquid and solid state, measured in l or kg. Typically, these residuals are used as fertilizers in agriculture.

Concerning the inputs, it is important to investigate the proportion of input quantities (measured in kg) compared

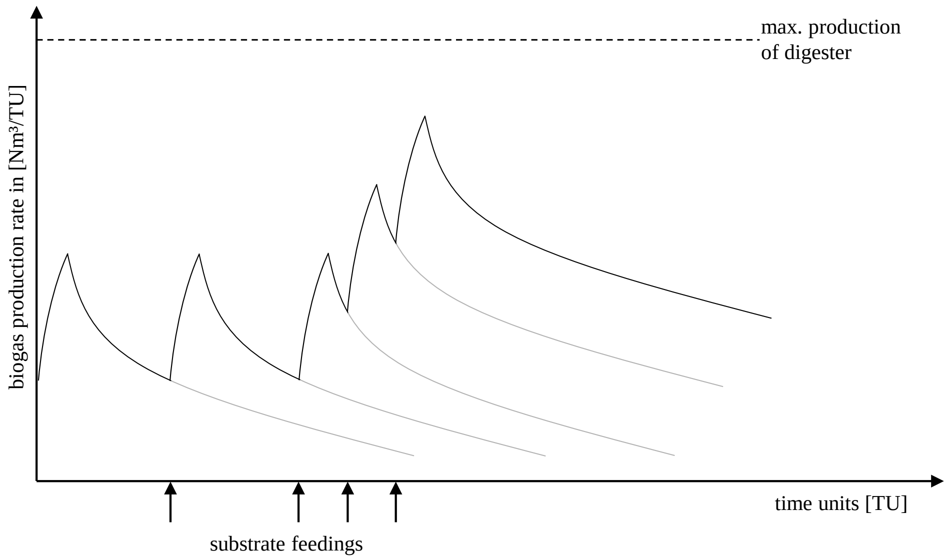

Figure 4.3: Characteristic variable biogas production rates (Mauky et al., 2017)

to the digester size. Therefore, density or volumetric weight is used. This measure defines the weight in kg per required space in m^3. Typical densities are for example 700 kg/m^3 for maize silage or 500 kg/m^3 for grass silage. (Kuratorium für Technik und Bauwesen in der Landwirtschaft e. V., 2018) These densities have to be compared to the digester size given in m^3. Even small biogas plants, like the one which is investigated in Section 4.5, can be characterized by digestion volumes of around 900 m^3. Hence, a tremendous amount of feeding is possible and the substrate is only disposed by the spillover after the digestion process is finished. This is realized by a biomass feed in at the bottom of the digester. Through further feedings, the previously contained biomass is transported to the top and is finally discharged through the spillover after completion of the digestion process. The agitator ensures that new fed substrate is digested first and not directly extracted using the spillover. In terms of outputs, the above explained characteristics apply. This means that the total gas yield and the time, which is needed to produce this gas, depends on the fed substrate.

Because the capacity is hard-constraint, a maximum feeding quantity had to be assumed. (Mauky et al., 2016) However, this maximum quantity is never binding because there is a more restrictive constraint concerning microorganisms. The biology in the digester is characterized by several microorganisms. Too much substrate input can destroy them. Hence, a maximum feeding quantity per time unit has be assumed to ensure, that the biology is not overloaded and the maximum production of the digester is considered.

4.2.2 Challenges and opportunities

The market conditions in the German energy market determine the framework for market participation opportunities of a biogas plant operator. Generally, there are several possibilities to participate in this market. The regulations of the energy market are defined in the renewable energy resources act (EEG). Firstly, a biogas plant operator can take the EEG feed-in tariff, which is a fixed compensation per kWh of produced electricity in the first 20 years of plant operation. As the majority of the existing plants are running with a conventional and inflexible configuration, these plants mostly use this way of participation. All other market participation possibilities require a flexibly schedulable operation of the biogas plant. These market participation possibilities can be subsumed as direct marketing. Here, it is either possible to participate in one of the three reserve markets, or in one of the markets at the energy exchange. At the energy exchange, the long-term option market, the day-ahead market, and

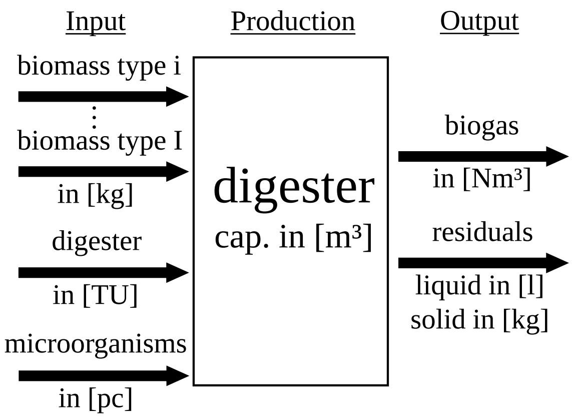

Figure 4.4: Digestion process

the intraday market can be distinguished. (Fichtner and Meyr, 2019)

A biogas plant operator of an existing plant, which is less than 20 years in operation, has several incentives to participate in direct marketing. The German government offers the first incentives. Here, the biogas plant operator can request two subsidies, market premium and flexibility premium. The market premium is a quantity-based subsidy while the flexibility premium is a capacity-based subsidy. Apart from these subsidies, the biogas plant operator has the opportunity to generate more earnings because of fluctuating energy spot market prices. As extensively explained by Fichtner and Meyr (2019) the prices at the energy spot market are characterized by three seasonalities (intrayear, intraweek, intraday). These fluctuations can be used to produce and sell electricity in high price periods, in order to generate as many earnings as possible. (Fichtner and Meyr, 2019)

Aforementioned, it can be beneficial for a biogas plant operator to participate in direct marketing. However, therefore a flexible biogas plant configuration, as given in Figure 3.3, is necessary. Fichtner and Meyr (2019) have shown how a conventional biogas plant can be adjusted to a type II plant, to participate in the day-ahead market. Nevertheless, further potentials exist by reaching a type III instead of a type II plant. If the biogas production process is flexibilized, less biogas storage capacities are required, because the biogas production is more similar to the biogas usage as input of the demand-oriented electricity production in the CHP plants. The reduction of the necessary storage capacity decreases the total investment for the plant adjustment as well. (Grim et al., 2015)

In order to support the investment decision of adjusting a conventional biogas plant to a type III plant, several challenges have to be mastered. In contrast to the study of Fichtner and Meyr (2019), the biogas production process has to be explicitly modeled. As explained, previous studies have shown that substrate management can influence the biogas production rate. However, the reactions of the production rate can be retarded or non-linear. (Grim et al., 2015; Mauky et al., 2015) These characteristics have to be included in the mixed-integer linear optimization models. Additionally, the costs of variable substrate management have to be included. Here, variable costs for the substrate, fixed costs for each feeding event, and variable costs of the biogas production have to be distinguished, while the latter ones depend on the efficiency of the digester, which can be defined as the ratio of biomass input and biogas output. However, the efficiency of the digester is not fixed, if a variable substrate feeding is applied. Thus, the efficiency has to be modeled based on the current substrate mixture in the digester. To conclude, several extensions of the OBPP and SBPP models in terms of the biogas production process are necessary. These extensions are explained in Section 4.4.

4.3 Literature review

The objective of this work is to optimize the operational schedule of a biogas plant economically, while variable substrate feeding is applied. Thus, a type III biogas plant configuration is considered. The scheduling of the feeding events depends on the fluctuation of the energy spot market prices and thus the opportunity to generate as high earnings as possible. As in the approach of Fichtner and Meyr (2019), such an optimized operational schedule is necessary to strategically optimize the biogas plant design regarding the biogas storage and the additional electrical capacity.

Fichtner and Meyr (2019) have already extensively dealt with the economic and technical modeling of the biogas plant characteristics, the legal circumstances, and the strategic investment decision using an optimized operational schedule and the related literature. Their approach occupies a unique position, because – compared to related literature – uncertain spot market prices are considered in the operational and strategic planning problems using a scenario approach. In order to economically optimize the operational biogas plant schedule considering variable substrate feeding, the approach by Fichtner and Meyr (2019) is used as a basis. To include a variable biogas production in this approach, further – rather technically focused – literature with the focus on the variable substrate feeding process is analyzed.

This further literature is evaluated concerning the following categories, given in Table 4.1: Firstly, the research scope of the investigated publications is analyzed. An analysis of variable biogas production in the digester (dp), an adjusted plant design (pd) based on the variable biogas production, the monetary implications of variable substrate feeding for the biogas plant operators (mon) and an operations research-based optimization (opt) of the operational schedule or the biogas plant design are distinguished. Secondly, the type of considered biomass feedstock is examined. The following nine biomass feedstocks are distinguished: Briquetted meadow grass (bmg), cattle manure (cm), cattle slurry (cs), effluent (effl), grass silage (gs), ground wheat grain (gwg), maize silage (ms), sugar beet (sb) and sugar beet silage (sbs). Additionally, the technical digestion method is analyzed. Therefore, a conventional continuously stirred tank reactor (CSTR) and adjusted digesters (adj.) are distinguished. Continuously stirred tank reactors are used as a common model for chemical reactions in the field of chemical engineering. Such a reactor is equipped with a mixing device to ensure efficient mixing of the substrate and often used as an idealized model of a tank reactor. (Schmidt, 1998) Adjusted digesters mean that the current digester setup (CSTR) has to be changed, for instance concerning the used filters or leach beds. (Linke et al., 2015; Lemmer and Krümpel, 2017) Besides, it is checked whether the respective study is executed within a full-scale or lab-scale system. Furthermore, the reaction time of the biomass production rate after a feeding event is measured. Finally, the literature is classified into long- (intrayear, year), mid- (intraweek, week), and short-term (intraday, day) variations of the biomass production rate.

Within the first publication by Grim et al. (2015) the influence of variable substrate feeding in the context of demand-oriented electricity production in biogas plants on the necessary biogas storage capacity is analyzed. Using several scenarios of the Swedish market, the conclusion was that the required storage capacity could be reduced using variable substrate feeding. An optimization of the operational biogas plant schedule or the plant design is not executed. Linke et al. (2015) investigated the technical potential of an innovative reactor for demand-oriented electricity production within a biogas plant. In this study, several feeding patterns are compared. As a conclusion, the authors are able to generate a robust and reliable biogas production rate. No economic effects or implications on the biogas plant design are considered. Within the study of Mauky et al. (2015) the objective was to identify feeding strategies for demand-driven energy supply in biogas plants. The lab-scale experiment shows that the necessary biogas storage capacity can be theoretically reduced by flexible biomass feeding. Nevertheless, this theoretical change is not economically analyzed or further optimized. Barchmann et al. (2016) analyzed the additional increase of flexibility in a biogas plant using flexible substrate management. Here, the economic effects are analyzed on the basis of the German market using a cost-benefit-analysis for predefined production scenarios consisting out of feeding and electricity production schedules. The conclusion of Barchmann et al. (2016) is that the profits out of direct marketing can be increased using variable substrate feeding. However, no optimization on the basis of uncertain spot-market prices is achieved. The published study by Mauky et al. (2016) is a full-scale application and thus an extension of the previously explained study from 2015. In this case, the main objective of the model is to identify the optimal sequence of feedings into the digester. Without evaluating the economic effects or optimizing the adjustment, the authors show technically that the necessary biogas storage capacity can be reduced using variable substrate feeding. Ahmed and Kazda (2017) analyze the demand-oriented electricity generation based on just-in-time biogas production. Therefore, easily degradable substrates like sugar beet silage are bio-chemically investigated. The result of the study shows that there is no time lag between the maximum biogas and methane production rates. Economic effects are not considered. Lemmer and Krümpel (2017) analyze possibilities to adjust the digestion techniques in order to realize an efficient variable biogas production without an analysis of economic consequences. The study of Mauky et al. (2017) is as well closely related to the two ones from 2015 and 2016. Within the study of 2017, a high level of intraday flexibility is demonstrated on full-scale. As a result of the study can be concluded that the process stability is not influenced by a flexibilized substrate feeding and thus a demand-oriented biogas production can be used to realize significant savings, for instance, in terms of reduced biogas storage capacity. However, the size and economic value of these savings are not further analyzed. Terboven et al. (2017) show in their technical study the development of a new biogas reactor for demand-driven electricity generation. The results of the study show that this new reactor is well suited for flexible biogas production. Economic effects are not considered. Feng et al. (2018) analyze the quality of the produced biogas based on variable substrate feeding on a technical level in a lab-scale experiment. Their results show that different biomass feedstocks lead to different reactions to the biogas production rate. However, it is possible to elevate the biogas production rate in a short-term planning horizon. Economic effects on the biogas plant schedule or the plant configuration are not included.

Variable substrate feeding is a rather new and innovative research area within the field of biomass use for energy purposes. As given in Table 4.1 ten related publications from 2015 to 2018 are dealing with this issue. Only two of these publications (Linke et al. (2015), Terboven et al. (2017)) consider only one biomass feedstock type. In all of the other publications, at least two feedstock types are considered. Moreover, the majority of the publications are based on conventional CSTR. Only in three studies (Linke et al. (2015), Lemmer and Krümpel (2017) and Terboven et al. (2017)) the digester is technically adjusted. The shares of full-scale and lab-scale studies are almost balanced. As given in the table, the reaction time of the biomass production rate on a feeding event is always lower than 24 hours, if specified. Based on these short reaction times, in all of the mentioned publications (except Terboven et al. (2017)) a mid- to short-term planning is possible. The existing literature is characterized by a technical, bio-chemical, engineering focus. Thus, only in two publications economic effects of variable substrate feeding are measured. In none of the publications an economic optimization is carried out.

To conclude, the literature concerning variable substrate feeding is still in its infancy. On the one hand, the technically oriented research on variable substrate feeding is very limited. On the other hand – to the best of our knowledge – no economically oriented literature exists, which considers variable substrate feeding in the biogas plant optimization, independent whether operational or strategic. However, the literature shows that very short reaction times of the biomass production rate are possible. These reactions seem to be independent of the considered mix of biomass feedstocks and can be realized using conventional CSTR's. These findings concerning the reaction time cause a new insight into the potential of variable substrate feeding. The concept of variable substrate feeding can be used to compensate for short- and mid-term intraday and intraweek fluctuations. Thus, it can significantly influence the operational schedule of a biogas plant.

Since, as mentioned, the economic aspects of variable substrate feeding have not been sufficiently analyzed in

Table 4.1: Related literature

author	research scope	biom. feedst.	digester CSTR	digester adj.	scale full	scale lab	reac. time	sched. horizon
Grim et al. (2015)	dp/-/mon/-	cm, sb	x		x		$\leq$ 6h	week
Linke et al. (2015)	dp/-/-/-	ms		x		x	-	week
Mauky et al. (2015)	dp/pd/-/-	cs, ms, sbs	x			x	$\leq$ 24h	week
Barchmann et al. (2016)	dp/-/mon/-	cm, ms	x		x		-	week
Mauky et al. (2016)	dp/pd/-/-	cs, ms, sb, gs, gwg	x		x		$\leq$ 1h	week
Ahmed and Kazda (2017)	dp/-/-/-	gs, sbs	x			x	$\leq$ 3h	week
Lemmer and Krümpel (2017)	dp/-/-/-	effl, ms, gs		x		x	$\leq$ 1h	day
Mauky et al. (2017)	dp/pd/-/-	cs, ms, sb, gs, gwg	x		x		$\leq$ 1h	week
Terboven et al. (2017)	dp/-/-/-	sbs		x		x	$\leq$ 1h	-
Feng et al. (2018)	dp/-/-/-	ms, bmg	x			x	$\leq$ 24h	week

existing research, this will be done in the present study. Therefore, the approach by Fichtner and Meyr (2019) is used as a basis for the operational and strategic biogas plant optimization. Additionally, the findings and conclusions of the rather technically oriented studies out of Table 4.1 are used to combine the technical and economic points of view. Especially, the assumptions and conclusions by Mauky et al. (2017) will be used to include the process of variable substrate feeding into the operational (OBPP) and strategic (SBPP) optimization problems within a biogas plant. The reasons are that Mauky et al. (2017) show that several biomass feedstocks can be used to realize a reaction of the biogas production rate within a reaction time under one hour, which offers the possibility of a short-term biogas production scheduling. The results are not restricted to a few feedstocks and as a consequence general applicable for a lot of biogas plant operators, because the availability of feedstock types can be individually different. Additionally, the study is executed within a full-scale plant with a conventional CSTR. If the digester is technically adjusted, further investments are necessary. As the literature show, this adjustment is not necessary. Hence, this investment decision will be neglected.

4.4 Optimization considering variable substrate feeding

In Section 4.4 variable substrate feeding is considered in the optimization approach of Fichtner and Meyr (2019). Therefore, the variable biogas production rates are approximated in the first step in Section 4.4.1. In a second step, this approximation is included into the optimization models OBPP and SBPP.

4.4.1 Approximation of variable biogas production rates

As explained in Section 4.2.1, the resulting biogas production rates based on variable substrate feeding follow a non-linear pattern. In order to consider them in a linear optimization model, a linear approximation is necessary. One popular approach to achieve such an approximation is the application of piecewise linearization. According to the literature, various applications for piecewise linearization exist. For example, the following applications may be mentioned: transportation costs, inventory costs, or production costs in supply chains. However, not only non-linear cost functions can be approximated using piecewise linearization. Other applications can be found in operation or production planning. (Lin et al., 2013) Several applications require several solution approaches. Thus, the field of piecewise linearization combines several specific approaches for approximation. According to Birge and Louveaux (1997), Bradley et al. (1992) and Domschke et al. (2015),these approaches can be divided into the basic idea and possible variations. Generally, the idea is to approximate a non-linear function, given in Figure 4.5 as $f(x)$, using a piecewise linear function $L(f(x))$. This piecewise linear function is characterized by several segments or intervals ($k = 0, 1, ..., m-1$), which are limited by so-called break points (a_k). These break points define the upper (a_{k+1}) and lower boundary (a_k) of the segment. Within a segment, the slope of the original non-linear function is approximated by a linear one. Therefore, the slope (s_k) within the segment is calculated using the upper and lower break points as follows:

$$s_k = \frac{f(a_{k+1}) - f(a_k)}{a_{k+1} - a_k} \qquad \forall k \quad (4.1)$$

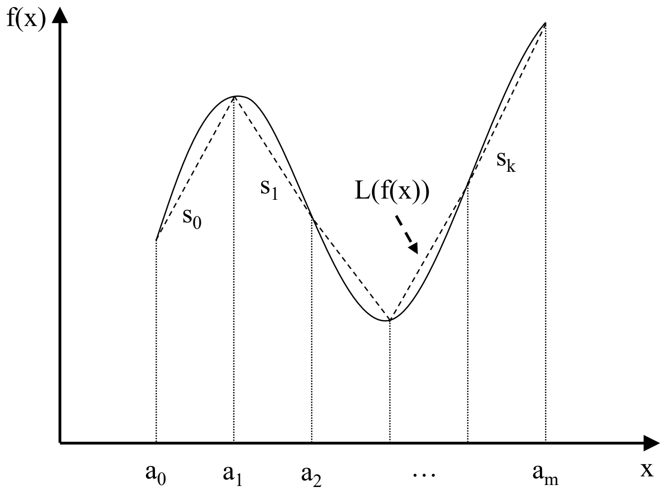

Figure 4.5: Piecewise linearization (Lin et al., 2013)

Combining this information for all segments, the entire non-linear function $f(x)$ can be approximated. Although, several variations of this basic approach exist. In the example, depicted in Figure 4.5, the segments are equidistant. This is not necessary. Sometimes it can be beneficial to chose the length of the segments according to the characteristics of the non-linear curve. Regarding the example in Figure 4.5, for instance, the third and the fifth break point could be neglected. Thus, the break points would be chosen according to the maximum and minimum turning points of the curves, which results in different lengths of segments. An approach with non-equidistant segments is discussed by Helber et al. (2013). Furthermore, the number of segments can be varied. In general, more segments lead to a better approximation. However, they can increase the solution time of the problem, the approximation is implemented in. The reason is that binary variables may be necessary to build the segments in which the non-linear function is approximated by a piecewise linear one. These binary variables make the problem much more difficult to solve. Therefore the best possible compromise must be found between the solvability of the problem represented by the number of binary variables on the one hand, and the quality of the approximation on the other hand. (Lin et al., 2013) Moreover, a distinction between an inner and outer linearization is possible. Within Figure 4.5 an inner linearization approach is applied. In contrast, an outer linearization would use tangents outside of the non-linear function to approximate the curve. (Bradley et al., 1992) Additionally, the approximation does not necessarily have to be two-dimensional. Kressner (2017) used in his PhD thesis a three-dimensional approach. In this case, a non-linear surface is approximated by linear planes. Another approach to increase the quality of the approximation is the choice of the approximated non-linear function. In this work, non-linear biogas production rates have to be approximated. Instead of approximating the biogas production rates directly, it could be beneficial to approximate the absolute biogas production within a segment to decrease the approximation error. Thus, not the slope of $f(x)$ is approximated, but the integral of $f(x)$ from a_k to a_{k+1}.

In order to evaluate the approximation error, the differences, or in other words residuals, between $f(x)$ and

$L(f(x))$ have to be investigated. As these differences can be positive or negative, a summation of absolute residuals leads to a biased result. Thus, measures like the mean-squared-error (MSE) or root-mean-squared-error (RMSE), normally used to evaluate forecasting errors, can be used to evaluate the quality of the approximation. In both cases, the residuals are squared in a first step, thus, the resulting squared residuals are always non-negative.

In this work, it is necessary to approximate the non-linear variable biogas production rates, resulting by variable substrate feeding. As depicted in Figure 4.3, these production rates are varying over time. Additionally, they are different for each biomass feedstock and feeding quantity. In order to approximate each influence individually, an approximation for each feedstock and each feeding quantity with respect to the time is necessary. Thus, a two-dimensional approach (biogas production rate over time) is used. Additionally, an equidistant approach is chosen with a segment length of one hour. This choice relates to the characteristics of the optimization models, explained later on in Section 4.4. In these models, the granularity is hourly and fixed. In the remainder, two two-dimensional approaches are compared. The first one is a direct approximation of the biogas production rate using a piecewise inner linearization. The idea of the approach is depicted in Figure 4.6 chart a). The second approach does not approximate the slope of the biogas production rate, but the produced biogas in total. Therefore, the area below the curve is approximated. (see Figure 4.6 chart b))

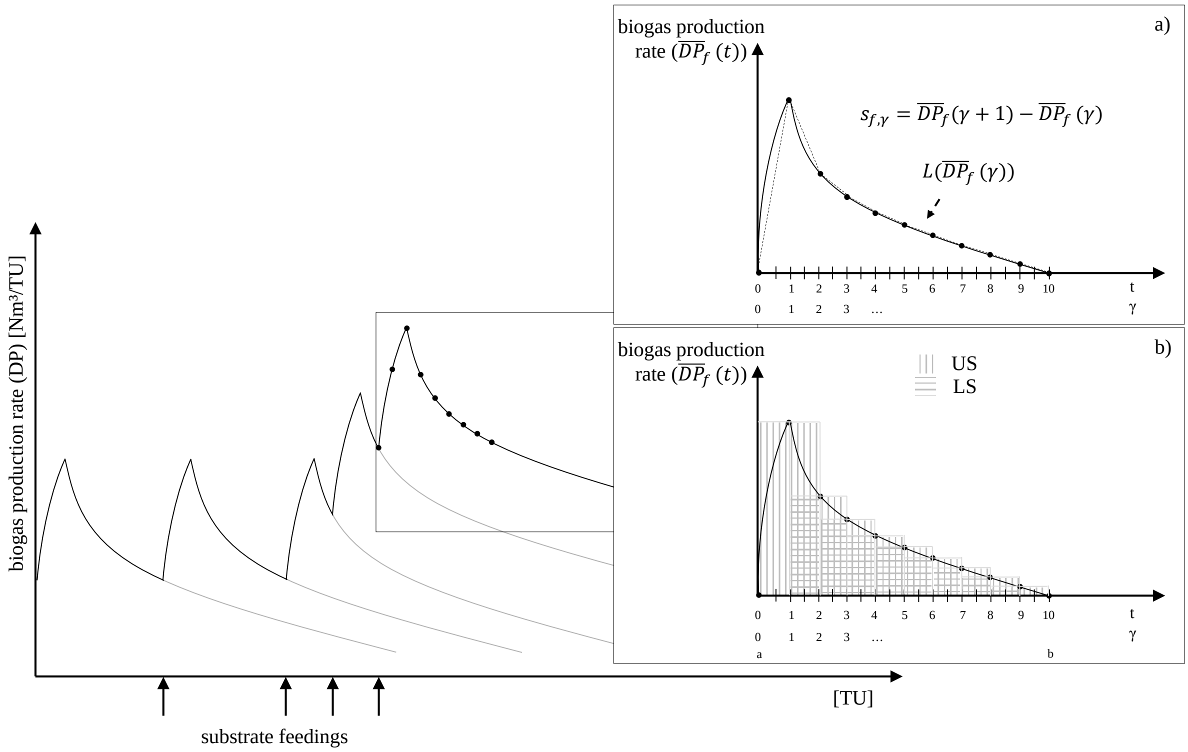

Figure 4.6: Approximation of variable biogas production rates (Mauky et al., 2017)

In Figure 4.6 chart a) the retrospectively observed biogas production rate ($\overline{DP}_f(t)$) with regard to the time $t \geq 0$ after feeding is depicted. The new index $f = 1,...,F$ is used to differentiate between several biomass feedstocks. The discretized microperiods after feeding are defined as $\gamma = 0,1,2,...,\Gamma$. As shown, the biogas production rate follows a non-linear pattern. In order to model this characteristic, the idea of piecewise linearization can be used. That means that the development of the biogas production rate after a feeding event is split into discrete time intervals. These time intervals are used to define equidistant segments to approximate the non-linear biogas production rate. The total time after a feeding event Γ is defined as the influencing time of the fed substrate. Within the first periods after a feeding event the biogas production rate is characterized by a fast in- and rapidly decrease.

Afterward, an approximately constant decrease appears in the upcoming periods. In each segment after a feeding event, the slope of the curve of the biogas production rate can be approximated with $s_{f,\gamma}$. The calculation is equal to Equation (4.1) with a segment length of one. The slopes in the segments within the influencing time build up the approximation of the non-linear biogas production rate, defined as $L(\overline{DP}_f)$. To conclude, the first approach combines the idea of equidistant segments within an inner linearization.

In contrast to the explained first approach, the second one does not directly approximate the biogas production rate. Instead, the produced biogas per segment is approximated. The produced biogas in total within the interval [a,b], or in other words the area below the graph, shown in Figure 4.6 chart b), is defined as $\overline{DP}_f^{tot}$. The according calculation is defined in Equation (4.2). Again, the function $\overline{DP}_f(t)$ is defined as the digester production rate of feedstock f after t time units after feeding.

$$\overline{DP}_f^{tot}(b) = \int_a^b \overline{DP}_f(t)\ dt \qquad \forall f \quad (4.2)$$

In order to approximate the integral, representing the produced biogas in total, the idea of Riemann sums is applied. (Riemann, 1867) Therefore, the time after a feeding event is again divided into equidistant segments called γ. In each segment, rectangles can be used to approximate the area below the graph. The problem is, that the height of the area within a segment is not constant. Thus, several possibilities exist to choose the height of the rectangles: For example, either the highest or lowest point in each segment could be chosen. In case, the highest point is chosen, the so-called upper Riemann sum (US) is applied. If the lowest point is selected, it is the lower Riemann sum (LS). As one can see in Figure 4.6 chart b), the upper sum overestimates the produced amount of biogas within a segment and the lower sum underestimates it. However, the real biogas production within a segment has to be between US and LS. Thus, the approximation error is limited to the difference between US and LS. In order to choose a specific approximation value within each segment, the average of US and LS is calculated. This average represents the area in the middle between US and LS. Thus, the approximation of $\overline{DP}_f^{tot}$ is defined as $A(\overline{DP}_f^{tot})$ in Equation (4.3). It is implicitly assumed, that the length of the segments is normalized to one.

$$A(\overline{DP}_f^{tot}(b)) = \sum_{\gamma=a+1}^{b} \frac{US(\overline{DP}_f(\gamma)) + LS(\overline{DP}_f(\gamma))}{2} \qquad \forall f \quad (4.3)$$

In order to evaluate the approximation approaches, the approximation error is measured, which is the difference between the approximated values (for instance, $L(\overline{DP}_f)$ in approach a)) and the real values of the non-linear function. To evaluate the performance of the approximation approaches based on several behaviors of biogas production rates, three curves of fictional non-linear biogas production rates are assumed. For all three cases and the two approximation approaches the MSE and RMSE of the approximation error is analyzed. The two forecast quality measures are chosen to deal with both positive and negative deviations.

The three non-linear functions are used to model several possible behaviors of the biogas production rate with an impact on the approximation quality. All of the used datasets are characterized by the mentioned rapid in- and decreases of the biogas production rate, which are explained in Figures 4.3 and 4.6. The approximation of the resulting peak after a feeding is intended. Therefore, an exemplary horizon of 100 periods is assumed, which are divided into ten equidistant segments. The main difference between the three cases is the location of the production peak. The differentiation is intended to represent different characteristics of substrates that do not necessarily correspond to the idealized representation in Figure 4.6, where the production peak occurs exactly at a segment

Table 4.2: Evaluation of approximation approaches

	PL		RS	
	MSE	RMSE	MSE	RMSE
Peak 5	114.68	10.71	10.08	3.18
Peak 10	21.40	4.63	2.69	1.64
Peak 15	79.93	8.94	4.12	2.15

boundary. Thus, the influence of non-idealized cases can be measured. In the first case (Peak 10), the production peak is reached after ten periods, which is equal to the break-point between the first and second segments. This is an idealized assumption, which results in a very accurate approximation using piecewise linearization. In order to model non-idealized cases as well, cases with a production peak after five periods (Peak 5) and after 15 periods (Peak 15) are considered as well.

The results of the evaluation of the approximation approaches are depicted in Table 4.2. Here, PL represents the approach using piecewise linearization, and RS stands for approximation using Riemann sums. As shown, for all case-approach-combinations the MSE and RMSE are calculated. It is not surprisingly noticeable that both approaches lead to the best results in the idealized case with a production peak after an entire segment. The relative increase of the approximation error of the idealized case compared to the other cases is similar for both approaches but slightly bigger if piecewise linearization is applied. Nevertheless, the approximation approach using the Riemann sums performs better in every case.

In all of the three cases, biogas production rates between 0 and 150 Nm^3/TU are assumed, which leads to a biogas production in total of more than 400 Nm^3 in the considered time horizon in each case. The approach using Riemann sums performs better than the piecewise linearization. In order to measure the influence of the approximation approach concerning the biogas production rates on the optimization, both approaches are applied in the upcoming optimization models.

4.4.2 Extended optimization models

As identified in the related literature, the variability of the biogas production rate can influence the operational scheduling and hence the investment decision to increase the flexibility of the whole biogas plant. In order to investigate the economic influence of variable substrate feeding on a biogas plant optimization, the multistep optimization approach of Fichtner and Meyr (2019) is extended. In particular, the SBPP and OBPP models are adapted. Instead of modeling a type II biogas plant, characterized by a steady and inflexible biogas production rate, in the remainder, a variable biogas production rate and thus a type III biogas plant is considered. As depicted in Figure 4.2, the only difference between a type II and type III plant is the variability of the biogas production rate.

The general procedure of the multistage optimization approach by Fichtner and Meyr (2019) will not be changed. The changes relate only to the deterministic optimization part, which consists of the OBPP model to optimize the operational biogas plant schedule and a strategic SBPP concerning the investment decision. The optimized operational plant schedules are used to evaluate several investment strategies in the strategic part. Within the following extended models, the notation of the models by Fichtner and Meyr (2019) is adopted and adapted regarding the mentioned extension concerning the biogas production rate. In the remainder, the extended models will be called SBPP-VAR resp. OBPP-VAR, as they are a reformulation of the deterministic SBPP resp. OBPP models with variable substrate feeding. The general idea within the optimization approach of Fichtner and Meyr (2019) remains unchanged. That means that an untypical detailed modeling of the operational schedule is necessary to evaluate the strategic investment decisions. The reasons for that characteristic are that, on the one hand, the design of governmental subsidies and on the other hand, the modeling of the development of the biogas production rate make it necessary to simulate an operational schedule on a very detailed level. Thus, common aggregations in strategic optimization models are not possible in this case.

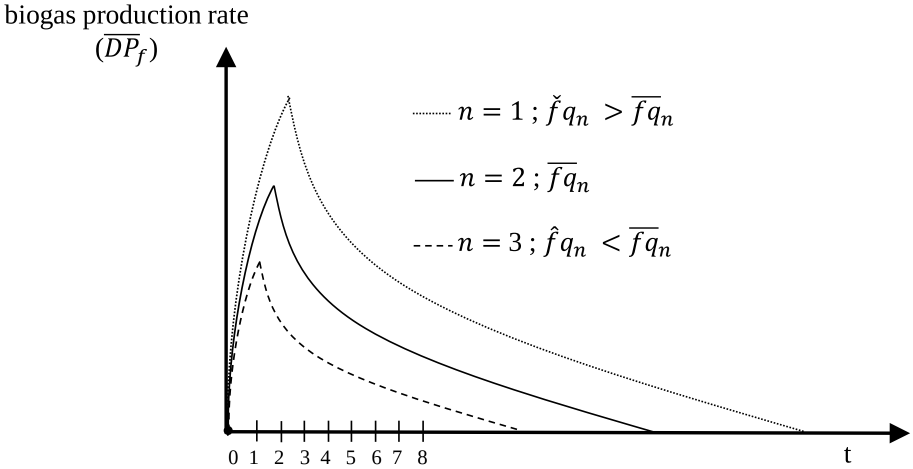

Figure 4.7: Quantity-depending scaling up and down

In the last Section 4.4.1 is discussed how the non-linear development of the biogas production rate after a feeding of a specific feedstock quantity can be approximated. It is explained that the biogas production rate changes during the time after feeding. In addition to this time-depending effect, a quantity depending effect has to be considered. This effect is depicted in Figure 4.7. Here, the index $n = 1,...,N$ is used to define size categories for feeding quantities fq_n. These feeding quantities of a biomass feedstock can be interpreted similarly to lotsizes in a production planning problem. In the given example in Figure 4.7, $n = 2$ numbers as a basic feeding quantity $\overline{fq}_n$. Compared to this feeding quantity, the quantities in size category $n = 1$ are higher ($\check{f}q_n$) resp. lower in case of category $n = 3$ ($\hat{f}q_n$). The characteristic influence of the feeding quantity on the biogas production rate is as follows. If more feedstock is fed into the digester, the characteristic increase of the biogas production rate and thus the production peak is disproportionately high. Thus, the resulting biogas production rate after a feeding event depends not only on the time after feeding, but also on the size category of the feeding quantity. Accordingly, the approximation values for the biogas production rate can be adapted to consider the feeding quantity effect. Hence, the adapted definitions are $L(\overline{DP}_{f,n})^{scale}$ and $A(\overline{DP}^{tot}_{f,n})^{scale}$, where $scale$ means that the quantity depending effect of a feeding of category n is considered.

Aforementioned, the biogas production rate can be influenced by a feeding event for a limited time interval, which is called influencing time in the remainder. The modeling idea of the influencing time is shown in Figure 4.8. Within the figure, a timeline for the planning horizon is given. This planning horizon is divided into equidistant, non-overlapping time periods $s = 1,...,S$. Each time, a feeding event takes place, an influencing process on the biogas production rate with a defined influencing time is started. Thus, the feeding event characterizes the starting signal for the beginning of the influencing time. Additionally, a feeding event, characterized by a feeding quantity of a feedstock type, is rated with costs, which cause payouts. The counter index $\gamma = 0,...,\Gamma$ is applied to define the periods after a feeding event within the influencing time interval Γ. Only during this influencing time, the biogas production rate is stimulated by the related feeding event. The influence on the biogas production rate within the influencing time can be measured and approximated as discussed in Section 4.4.1. The produced amount of biogas can subsequently be used to produce electricity demand-oriented. The selling of the electricity is then rated with payments. Hence, the produced biogas can be rated with a future payment potential. Outside of the influencing time, no influence on the biogas production rate has to be measured. In order to calculate the accumulated influence of several feedings on the biogas production rate in total within a specific microperiod $s = \eta$, it is necessary to check whether this microperiod is part of one or several influencing times of previous feeding events. If this is the case, the time after feeding has to be measured using γ. Applying this information on the approximation approaches, explained in Section 4.4.1, leads to the specific influencing quantity on the biogas production rate. In other words, the approximation approaches are necessary to obtain an idea of the development of the influencing quantity on the biogas production rate. The modeling of the influencing time using the counter index γ as the mentioned variable time grid is necessary to define the point in time within the approximated development.

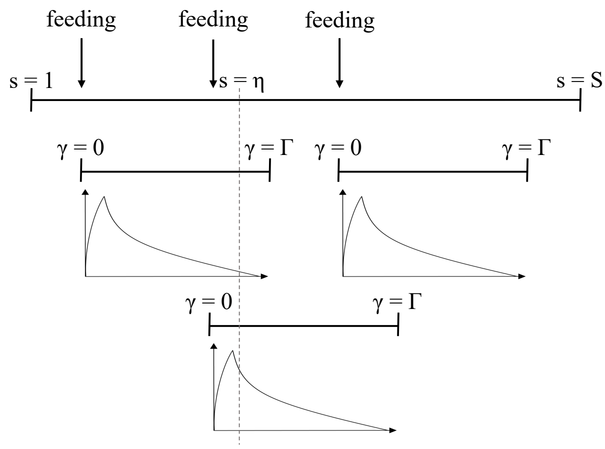

Figure 4.8: Modeling of influencing time

Approaches to similar problems can be found in the literature. For instance Popp (1983) measures the effect of sales signals as part of a strategic sales and investment planning. In this approach, the sales signal defines the starting impulse of volatile demand effects within a limited time after the signal. Thus, the sales signals are similar to the feeding events in the current work and the demand effects relate to the influenced biogas production rate. Additionally, related problems can be found in literature concerning lotsizing considering ramp-up phases. In this case, the feeding quantity can be interpreted as a specific production lotsize and the feeding event as the production start of this lot. The ramp-up phase, typically characterized by an increased efficiency based on learning effects, can then be interpreted as a limited time interval after production starts, similar to the influencing time. (Almgren, 1999; Fjällström et al., 2009; Glock et al., 2012; Matta et al., 2007) The major difference between the production quantities during a ramp-up phase after starting a lotsize and the biogas production rate during the influencing time is that production quantities in ramp-up phases are characterized by an increase until a steady-state system is reached. After this point, the production quantities remain stable at this level. In contrast, the biogas production rates within the influencing time are characterized by rapid in- and decreases, until the effect expires. Additionally, in contrast to ramp-up phases, influencing times of feeding events can overlap as depicted in Figure 4.8. The major similarity of both problems is the decomposition of the planning horizon into limited time intervals (ramp-up phase, influencing time) and the remaining time and the measurement of effects only within these first time intervals.

As explained during the previous sections, the consideration of variable substrate feeding leads to several extensions and adjustments concerning the modeling. Therefore, further data is necessary. At first, a new time interval, in contrast to the approach developed in Chapter 3, is needed to model the microperiods at one day. Therefore the new index $d = 1, ..., D$ for days and the new subset $\Phi_d \subset \Phi$, which defines the specific hours of each day, are included. The biogas production rate is no longer assumed as being constant. In order to model a variable biogas production rate, it is necessary to define the flow of biomass feedstock into the digester. Therefore, it is necessary to distinguish between different biomass feedstocks as substrate. As mentioned, the new index $f = 1, ..., F$ is used to differentiate between several biomass feedstocks. As previously explained, the counter index $\gamma = 0, ..., \Gamma$ is applied to define the periods after a feeding event within the influencing time interval Γ. Several biomass types can be used as substrate in the digester. The costs for these types c_f^F (in EUR/kg) have to be distinguished because they can be different. For instance, the costs for biowaste are lower than for maize silage. The quantity-dependent costs of the feeding into the digester, for example using a wheeled loader, are included in c_f^F as well. In addition to the costs for biomass feedstocks, operating costs for the digester c^G in (EUR/h) and variable electricity production costs within the CHP plant c^E (in EUR/kWh) have to be distinguished. The feeding quantity of the substrate into the digester is assumed as a variable. Aforementioned in Section 4.2.1, the digester capacity has not to be specifically modeled. Nevertheless, in order to ensure biological process stability in the digester, the daily feeding quantity is limited to X^{FDmax}.

In addition to the previously considered indices and cost parameters, further parameters are necessary to model the variable biogas production process within the digester using the two considered approximation approaches PL and RS. In case PL is applied, the parameter $\alpha_{f,n,\gamma}$ is considered. This parameter represents the slope of the approximated non-linear biogas production curve, defined as $s_{f,\gamma}$ in Section 4.4.1, divided by the feeding quantity of a feedstock type f out of size category n, and only defined for the periods during the influencing time. Thus, the dimension of $\alpha_{f,n,\gamma}$ is $Nm^3/kg \cdot h$. As previously explained, several feeding quantities fq_n of size categories n in kg are distinguished. In case RS is applied, the parameter $\beta_{f,n,\gamma}$ is considered. This parameter represents the produced biogas quantity using a feeding quantity out of size category n of feedstock f within a period/segment after feeding γ in Nm^3/h.

Within the extended OBPP-VAR and SBPP-VAR models, compared to the OBPP and SBPP models, another decision stage concerning the decision about variable substrate feeding is included. In order to model this decision, the new variable $X_{f,s}^{FD} \geq 0$ is used to model the flow of a specific biomass feedstock into the digester in kg in a microperiod. Within the extended models, the biomass transformation process from solid biomass into liquid biomass, shown in Figure 4.2, is not considered. It is assumed that several types of biomass are available, which are characterized by different conversion rates. The choice concerning a biomass feeding of type f and size category n in a microperiod s is represented by the binary variable $FC_{f,n,s} \in \{0,1\}$. In addition to the biomass feedstock flow into the digester, the relationship between biomass feeding and biogas production has to be defined to model the variable biogas production rate. This production rate out of a biomass feedstock f within a specific microperiod s ($DP_{f,s} \geq 0$) depends on the amount and point in time of previous feeding events. Thus, this biogas production rate is mutable. The relationship between the new substrate feeding variables, biogas production, and the existing decision variables is depicted in Figure 4.9

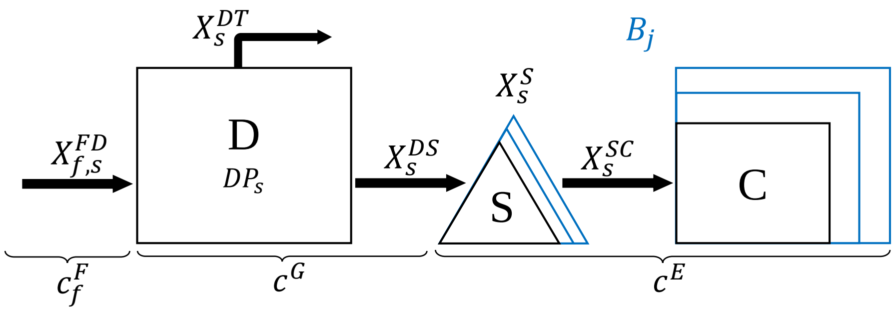

Figure 4.9: Structural / operational variables and cost structure of OBPP-VAR/SBPP-VAR

The whole notation of the OBPP-VAR and SBPP-VAR models is given the appendix. Within Table 4.3, only the additional notation compared to the OBPP resp. SBPP is shown. The parts of the notation, which were not mentioned in detail, remain the same as in the models in Chapter 3. In the following, only the adjusted and extended parts of the models compared to the OBPP and SBPP by Fichtner and Meyr (2019) are explained in detail. The entire models are provided in the appendix as well.

Table 4.3: Additional notation OBPP-VAR and SBPP-VAR

Indices	
$d = 1,...,D$	meso periods, days (d) in the planning horizon
$f = 1,...,F$	available biomass feedstock types as substrate
$n = 1,...,N$	size categories of feeding quantities of feedstocks
$\gamma = 0,...,\Gamma$	counter index, last microperiods after a feeding event within the influencing time interval Γ
Sets	
Φ	set of all microperiods
$\Phi_d \subset \Phi$	set of all microperiods in meso period d
Parameters	
$\alpha_{f,n,\gamma}$	time depending biogas change of the biogas production rate per kg using a feeding quantity of category n and feedstock f in period γ after a feeding event in $Nm^3/kg \cdot h$
$\beta_{f,n,\gamma}$	produced biogas quantity using feedstock f with feeding quantity of category n in period γ after a feeding event in Nm^3/h
c^E	electricity production costs of a specific biogas plant (variable costs) EUR/kWh
c^F_f	costs for used biomass feedstock f incl. feeding in EUR/kg
c^G	operating costs for digester in EUR/h
fq_n	discrete feeding quantity input into digester in size category n of a feedstock in kg
X^{FDmax}	maximum feeding quantity per day in kg
Decision Variables	
$DP_s \geq 0$	biogas production rate in the digester per microperiod s in Nm^3/h
$FC_{f,n,s} \in \{0,1\}$	decision variable, 1 if feeding quantity of category n of feedstock f in microperiod s is chosen, 0 otherwise
$NPV \geq 0$	objective value SBPP-VAR
$X^{FD}_{f,s} \geq 0$	flow of biomass feedstock f into the digester in kg in microperiod s

Objective function OBPP-VAR:

$$Max \quad \sum_s \underbrace{(p_s + m_s) \cdot a \cdot X^{SC}_s}_{SMP_s} - VEGP_s + \underbrace{pr_s}_{ESP_s} \tag{4.4}$$

$$VEGP_s = \sum_f X^{FD}_{f,s} \cdot c^F_f + c^G + X^{SC}_s \cdot a \cdot c^E \tag{4.5}$$

Objective function SBPP-VAR:

$$Max \quad NPV = \\ \sum_j \sum_s \frac{(p_s + m_s) \cdot a \cdot X_s^{SC} - VEGP_s + pr_s}{(1+i)^s} - \underbrace{\frac{dr_s}{(1+i)^S} \cdot B_j \cdot I_j}_{LOV} \tag{4.6}$$

Similar to the OBPP model by Fichtner and Meyr (2019), the objective function (4.4) of the OBPP-VAR model is used to maximize the sum of the spot market payments (SMP_s) and expected subsidy payments (ESP_s) reduced by the variable electricity generation payouts ($VEGP_s$) within the entire planning horizon. In contrast to the OBPP model by Fichtner and Meyr (2019), the calculation of $VEGP_s$ is adjusted, because the biogas production rate is no longer assumed as being stable. Thus, biogas production costs can no longer be represented as a fixed parameter. This adjusted understanding of the biogas production costs leads to an adaption of $VEGP_s$. As the produced biogas is either used for electricity production or burned in the torch and the torch payouts are determined by the variable biogas production costs, these costs are implicitly considered in $VEGP_s$ and have not to be included as a separate term.

The $VEGP_s$ per microperiod in the OBPP-VAR model are defined as the sum out of the biomass feedstock costs, the operating costs of the digester, and the electricity generation costs in the CHP plant (see Equation (4.5)). Although the operating costs for the digester are quantity independent and are thus not relevant for the decision of the operational biogas plant schedule, these costs are considered, because they are subsequently necessary to decide whether the net present value (objective value of the SBPP-VAR) is positive or negative. These costs are mainly determined by the heating of the digester, which has to be ensured at every filling level.

Within the developed optimization approach by Fichtner and Meyr (2019) the optimization of the operational plant schedule is a crucial part of the strategic optimization, to be able to calculate potential future payments and payouts and thus to evaluate different investment strategies. Hence, the objective value of the SBPP-VAR model, which should be maximized, represents the NPV (see Equation (4.6)). The payments and payouts appear at different points in time. In order to make them comparable, they are discounted. As in the basic SBPP model, the discounted SMP_s, the discounted $VEGP_s$ (including torch payouts) and discounted ESP_s are modeled. Instead of the OBPP model, the modeling of the previously explained OBPP-VAR model is applied. Additionally, the total loss of value (LOV) is considered in the last part of the objective function.

Constraints:

Mass balance

$$DP_s = X_s^{DS} + X_s^{DT} \qquad \forall s \tag{4.7}$$

$$DP_s = DP_{s-1} + \sum_f \sum_n \sum_\gamma f q_n \cdot FC_{f,n,s-\gamma} \cdot \alpha_{f,n,\gamma} \qquad \forall s^5 \tag{4.8}$$

[5]If PL is applied.

$$DP_s = \sum_f \sum_n \sum_\gamma FC_{f,n,s-\gamma} \cdot \beta_{f,n,\gamma} \qquad \forall s^6 \quad (4.9)$$

$$X^{FD}_{f,s} = \sum_n fq_n \cdot FC_{f,n,s} \qquad \forall f,s \quad (4.10)$$

$$\sum_f \sum_{s \in \Phi_d} X^{FD}_{f,s} \leq X^{FDmax} \qquad \forall s \quad (4.11)$$

$$\sum_f \sum_n FC_{f,n,s} \leq 1 \qquad \forall s \quad (4.12)$$

Parts of the basic OBPP and SBPP models can be used without adaptions in the OBPP-VAR resp. SBPP-VAR models. These unadapted parts are not presented in detail again. The focus within the present section is on the adapted and extended constraints regarding the variable biogas production based on variable substrate feeding. All of the mentioned and in the following in detail explained constraints are applied in the OBPP-VAR as well as in the SBPP-VAR.

The amount of the biogas production rate at the end of microperiod s is modeled in Constraint (4.7). It is ensured, that this amount is equal to the amount of produced biogas within microperiod s. Furthermore, this is equal to the amount filled into the biogas storage or burned in the torch.

The biogas production rate at the end of microperiod s is based on specific biomass feedings per microperiod and considered in Constraints (4.8) and (4.9). Using variable substrate feeding and thus changing feedings into the digester, the biogas production rate can be influenced. The biogas production rate within a specific microperiod is thereby determined by the biogas production rate at the end of the previous period and the change of the biogas production rate within microperiod s.

The effect per kg of a specific feeding quantity ($X^{FD}_{f,s}$, Constraint (4.10)) in a specific microperiod after the feeding event is defined as $\alpha_{f,n,\gamma}$, in case PL is applied. It is theoretically assumed, that the biogas production rates out of several substrates can be linearly summed up on average. In practice, deviations may occur because of a lack of calibrated measures of biomass feedstocks. The overall effect of a feeding event has to be divided into two sub-effects which are time- and quantity-depending. Both effects are represented by $\alpha_{f,n,\gamma}$ when PL is applied. In order to model the time-depending effect the index γ is used. Here, Γ is defined as the time after a feeding event, in which the biogas production rate is influenced by this feeding. This means that a time-dependent effect occurs when there was feeding event in a period $s-\gamma$. Furthermore, the quantity-depending effect can be considered using the index n for the size categories of feeding quantities fq_n. The decision concerning the chosen feeding quantity of a specific feedstock in a microperiod is modeled using the binary variable $FC_{f,n,s}$ (see (4.10)).

If the approximation approach RS is applied, DP_s is calculated differently, depicted in Equation (4.9). In this case, the quantity- and time-depending effects of a feedstock event are both considered in $\beta_{f,n,\gamma}$ as input data. Thus, $\beta_{f,n,\gamma}$ is defined for every feedstock, feeding quantity, and period after feeding within the influencing time. The consideration of $\beta_{f,n,\gamma}$ as a feeding influence is triggered by the binary variable $FC_{f,n,s}$. Hence, the total

6 If RS is applied.

Table 4.4: Numerical example Constraint (4.8)

Assumptions				**Calculations**	
				s	$DP_{1,s}$
F	1	N	1	0	50.00
Γ	22	$X^{FD}_{1,1}$	750	1	49.00
$DP_{1,0}$	50			2	94.88
γ	1	2	3	3	79.81
$\alpha_{1,1,\gamma}$	0.0625	-0.01875	-0.0125	4	69.44
γ	4	5		5	68.39
$\alpha_{1,1,\gamma}$	-0.0014	-0.0014		6	67.34

biogas production rate in a specific period can be calculated as the sum of all biogas production quantities based on previous feedings which occur in this specific period.

The maximum feeding quantity per day is modeled in Constraint (4.11). It is important, that the maximum feeding quantity of all considered feedstocks is lower than the maximum feeding quantity. Aforementioned in Section 4.2.1, this restriction is necessary to ensure the stability of the digestion processes based on the living microorganisms in the digester. Additionally, in each microperiod, only one feeding event with one specific feeding quantity of one specific feedstock type is allowed. (Constraint (4.12)) It is assumed, that the feeding quantity in the first size category is zero. This restriction implicitly ensures that the volume capacity of the digester is not exceeded because the largest feeding quantities are chosen in a way that this cannot happen with one feeding per microperiod.

A numerical example concerning Constraint (4.8) is depicted in Table 4.4 and Figure 4.10. There, the development of the biogas production rate is determined for an example with one feeding of one specific biomass feedstock and the PL approximation approach. As depicted in the related table and figure, a feeding event takes place in microperiod $s = 1$. Hence, the counter index γ starts in this period with $\gamma = 0$. The influencing time is assumed as $\Gamma = 22$. However, only the first five periods of the total influencing time are considered. Applying the given parameter values of $\alpha_{f,n,\gamma}$ the resulting biogas production rate can be calculated for every period after the feeding event. The input data is based on the study by Mauky et al. (2017). Within $\alpha_{f,n,\gamma}$ both the quantity- and time-depending effects of the feeding event are considered. The biogas production rate per microperiod can then be calculated according to Constraint (4.8) with the information of the previous biogas production rate and periodic change. In similar examples the modeled RS approximation approach in Constraint (4.9) could be applied. In contrast, not the time depending biogas change of the biogas production rate $\alpha_{f,n,\gamma}$ is necessary, but the absolute value of the produced biogas quantity in a period γ after feeding ($\beta_{f,n,\gamma}$). The remaining calculation is similar to the given example.

Within the extended models, material flows and storage levels can only take non-negative real values. Binary variables represent whether a feeding event takes place or not.

4.5 Numerical experiments concerning variable substrate feeding

In Section 4.5 the developed deterministic optimization models OBPP-VAR and SBPP-VAR are applied in numerical experiments. Therefore, the experimental design is characterized in the first step in Section 4.5.1. Afterward, several effects are separately analyzed. At first, the general effect of variable substrate feeding on the operational scheduling of biogas plants is investigated in Section 4.5.2. Afterward, the effects of different variably fed substrates on the operational schedules are analyzed in Section 4.5.3. Furthermore, the effects of several feedstock prizes are evaluated in Section 4.5.4 before a strategic planning based on variable substrate feeding is made in Section 4.5.5.

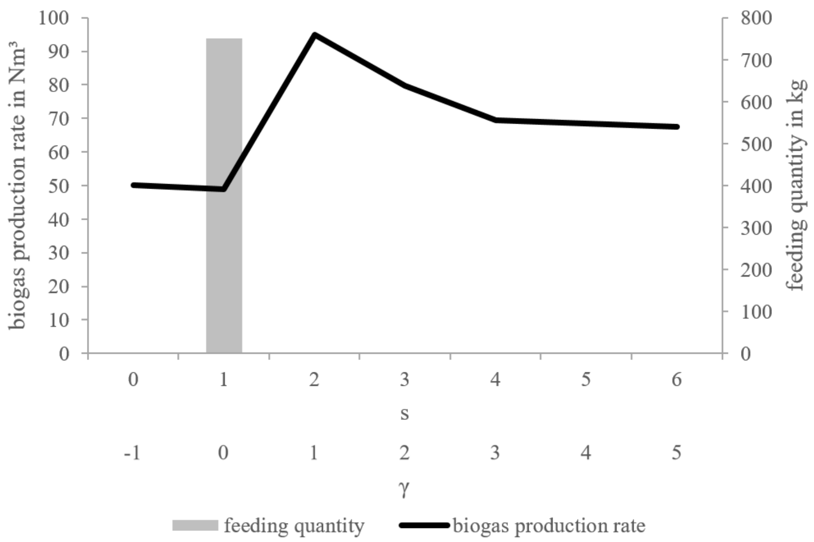

Figure 4.10: Graphical illustration of numerical example to Constraint (4.8)

4.5.1 Experimental design

In order to verify the performance of the developed optimization models, numerical experiments for a fictional but close to reality biogas plant are generated. The numerical experiments are based on several assumptions. These assumptions can be distinguished in assumptions concerning the variable biogas production and all further assumptions. The further assumptions are oriented on those specified by Fichtner and Meyr (2019). The investigated biogas plant is less than 20 years in operation. The specific biogas plant characteristics are depicted in Table 4.5. A rather small biogas plant with a currently installed CHP plant capacity of 192 kWh is assumed. Furthermore, a rated output of 75 % of the currently installed capacity is presumed. One Nm^3 biogas can be used to produce 1.52858 kWh of electricity. Moreover, the biogas and electricity production costs of the analyzed biogas plant are ascertained with $c^G = 0.02\ EUR/kWh$ and $c^E = 0.04\ EUR/kWh$. It is assumed, that at the beginning of the planning horizon the biogas storage is filled with 100 Nm^3 biogas, and the initial biogas production rate of the digester is 125 Nm^3/h. The biogas storage capacity is assumed to be sufficiently big so that it does not restrict the optimization. The idea is that the biogas plant operator changes the operational schedule from an inflexible to a flexible biogas production with variable substrate feeding. Thus, at the beginning of the planning horizon, the average biogas production for the unadjusted plant design is available. In order to model the decision of variable substrate feeding, five different feedstock types are distinguished. The first two ones are based on the results of a study by Mauky et al. (2017). These feedstocks are a mixture of maize silage and grass silage (ratio 1/3 maize 2/3 grass) ($f = 1$) and ground wheat grain ($f = 2$). Further, three additional fictional biomass feedstocks are considered. These feedstocks are used to simulate different characteristics like faster or slower in- and decreases of the biogas production and different biogas yields. Here, the first fictional feedstock ($f = 3$) is characterized by a rapid increase of biogas production after a feeding event, followed by a rapid decrease. In contrast, the third fictional feedstock ($f = 5$) is characterized by a very low but longer lasting increase of the biogas production rate. Thus, the biogas production rate is increased for a longer time interval. Another fictional feedstock ($f = 4$) is characterized by a behavior, which is a mixture of the first and the third. The costs for the first two real feedstocks are based on data by the FNR, Fachagentur Nachwachsende Rohstoffe e. V. (2009). The costs for the other three feedstocks are oriented on the average costs of feedstocks with similar characteristics. (FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2009) For discounting an interest rate of 2.76 % is assumed. (Deutsche Bundesbank, 2017) In order to calculate the terminal value at the end of the planning horizon, reducing balance depreciation with a yearly depreciation rate dr_s with $s \in \Phi_t^*$ is used. As given in Table 4.5 the yearly depreciation rates start with 30 % in the first year and end up with 7 % in the fifth. This is justified by the reason that machines like CHP plants have a higher loss of value in the first years of operation.

Aforementioned, the effect of a feeding event on the biogas production rate depends on the feedstock type, the feeding quantity, and the time interval after the feeding event. In order to model the feedstock as well as quantity- and time-depending effects, $\alpha_{f,n,\gamma}$ resp. $\beta_{f,n,\gamma}$ are used. (See Table 4.5). As the investigated biogas plant is rather small, only 5 size categories of feeding quantities between 0 and 1000 kg are distinguished. It is assumed in general, that if the feeding quantity is higher, the effect on the biogas production rate is greater. Based on a study from Grim et al. (2015), it is assumed that the pertinence of the change in the methane concentration of the biogas due to variable substrate feeding is very low. Thus, this change can be neglected.

Within Sections 4.5.2, 4.5.3 and 4.5.4 the developed OBPP-VAR is evaluated using numerical experiments. Therefore, a planning horizon of one week is assumed. The calculations are based on real market data of the day-ahead market in the first week of June 2016. In contrast, in Section 4.5.5 the SBPP-VAR is analyzed. Here, a generated scenario of the study by Fichtner and Meyr (2019), specifically the base scenario, is adopted as input data for the market prices. This scenario is generated using a manipulated forecasting function as explained in Chapter 3. By doing so, several potential market influencing changes in the future can be simulated.

It is explained in Section 4.4 that several discrete investment alternatives are distinguished within the developed SBPP-VAR model. For the calculations in Section 4.5.5, seven different storage versions and six different CHP plant versions are assumed. The specific capacities and the related amount of investments are shown in Table 4.6. The amount of investment for additional CHP plants is based on the published information by the FNR. (FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2017). The amount of investment for the biogas storages is based on prices from manufacturers. For both investment decisions is assumed that there is an alternative 1, which means that the plant design will not be changed. Furthermore, economies of scale are considered regarding the amount of investments. In addition to the described investments, a fixed infrastructure investment of 50,000 EUR is considered within the model, if one of the storages and/or CHP plants is installed. As explained, an investment alternative is characterized by a combination of one CHP plant capacity extension and one biogas storage. It is additionally assumed that the size of the biogas storage has to be large enough compared to the CHP plant capacity to keep the plant at least two hours running. Hence, 35 potential investment alternatives are possible. The planning horizon (T) is five years. The investment's depreciation time (DeT) is 10 years.

The numerical experiments are implemented in Python (2.7). The library Pandas is applied for data analysis. The solver Gurobi (7.5.1) is used together with the Pyomo (5.2) modeling tool interface. Experiments are run on a personal computer operated by Microsoft Windows 10 Professional, using an Intel CPU with 2.49 GHz and 8GB RAM.

4.5.2 Economic effects of variable substrate feeding

As explained in Sections 4.2.1 and 4.4, the biogas production rate can be influenced by a variation of the substrate-feeding interval, the substrate type, and the feeding quantity. This variation causes significant influences on the whole operational schedule of a biogas plant. Thus, the effects of variably fed substrates on the operational schedule are analyzed in the following.

In order to evaluate the OBPP-VAR model, weekly schedules are generated considering variable substrate feeding and with an inflexible biogas production process. Schedules considering variable substrate feeding are optimized using data of both discussed approximation approaches (PL and RS). The first real feedstock (maize/grass silage), explained in Section 4.5.1, is used. Weekly schedules ($S = 168$) are generated based on real market data.

Table 4.5: Biogas plant specific input data

a	1.52858 kWh/Nm^3				DP_0	125 Nm^3/h			
Bem^{init}	75 % of Cap^C				c^E	0.04 EUR/kWh			
c^G	0.02 EUR/kWh				Cap^C	192 kWh			
i	2.76 % p.a.				X_0^S	100 Nm^3			
s	8765	17530	26295	35060	43825				
dr_s	0.30	0.21	0.15	0.10	0.07				
f	1	2	3	4	5				
c_f^F	28	27	14	27	20				
γ	0	1	2	3	4	5	6	7	8
$\alpha_{1,1,\gamma}$	0	0	0	0	0	0	0	0	0
$\alpha_{2,1,\gamma}$	0	0	0	0	0	0	0	0	0
$\alpha_{3,1,\gamma}$	0	0	0	0	0	0	0	0	0
$\alpha_{4,1,\gamma}$	0	0	0	0	0	0	0	0	0
$\alpha_{5,1,\gamma}$	0	0	0	0	0	0	0	0	0
$\alpha_{1,2,\gamma}$	0	0.0078	-0.0003	-0.0008	-0.0048	-0.0019	0	0	0
$\alpha_{2,2,\gamma}$	0	0.0073	0.0049	-0.0018	-0.0034	-0.0011	-0.0048	-0.0011	0
$\alpha_{3,2,\gamma}$	0	0.0189	-0.0056	-0.0044	-0.0028	-0.0012	0.0048	0	0
$\alpha_{4,2,\gamma}$	0	0.0123	0.0043	0.0022	-0.0070	-0.0038	-0.0022	0	0
$\alpha_{5,2,\gamma}$	0	0.0075	0.0031	0.0020	0.0010	0.0005	-0.0045	-0.0036	-0.002
$\alpha_{1,3,\gamma}$	0	0.0082	-0.0003	-0.0008	-0.0025	-0.0025	-0.0021	0	0
$\alpha_{2,3,\gamma}$	0	0.0076	0.0051	-0.0019	-0.0036	-0.0012	-0.0025	-0.0025	-0.001
$\alpha_{3,3,\gamma}$	0	0.0199	-0.0059	-0.0046	-0.0029	-0.0012	-0.0025	-0.0025	-0.0003
$\alpha_{4,3,\gamma}$	0	0.0129	0.0045	0.0023	-0.0074	-0.0039	-0.0034	-0.0025	-0.0025
$\alpha_{5,3,\gamma}$	0	0.0079	0.0032	0.0021	0.0011	0.0005	-0.0057	-0.0047	-0.0044
$\alpha_{1,4,\gamma}$	0	0.0086	-0.0003	-0.0008	-0.0017	-0.0017	-0.0017	-0.0017	-0.0007
$\alpha_{2,4,\gamma}$	0	0.0079	0.0054	-0.0020	-0.0037	-0.0025	-0.0017	-0.0017	-0.0017
$\alpha_{3,4,\gamma}$	0	0.0207	-0.0062	-0.0049	-0.0031	-0.0013	-0.0017	-0.0017	-0.0017
$\alpha_{4,4,\gamma}$	0	0.0135	0.0047	0.0024	-0.0077	-0.0042	-0.0039	-0.0031	-0.0017
$\alpha_{5,4,\gamma}$	0	0.0083	0.0033	0.0022	0.0011	0.0005	-0.0060	-0.0049	-0.0045
$\alpha_{1,5,\gamma}$	0	0.0089	-0.0004	-0.0009	-0.0020	-0.0014	-0.0014	-0.0014	-0.0014
$\alpha_{2,5,\gamma}$	0	0.0083	0.0056	-0.0024	-0.0043	-0.0030	-0.0014	-0.0014	-0.0014
$\alpha_{3,5,\gamma}$	0	0.0216	-0.0064	-0.0050	-0.0039	-0.0021	-0.0014	-0.0014	-0.0014
$\alpha_{4,5,\gamma}$	0	0.0140	0.0048	0.0025	-0.0079	-0.0043	-0.0039	-0.0028	-0.0024
$\alpha_{5,5,\gamma}$	0	0.0086	0.0035	0.0023	0.0012	0.0010	-0.0065	-0.0055	-0.0036
n	1	2	3	4	5				
$\beta_{1,n,0}$	0	0	0	0	0				
$\beta_{1,n,1}$	0	1.936	4.069	6.374	8.811				
$\beta_{1,n,2}$	0	1.800	3.783	5.926	8.191				
$\beta_{1,n,3}$	0	1.599	3.363	5.267	7.280				

c_f^F in EUR/T; $\alpha_{f,n,\gamma}$ in Nm^3/kg; fq_n in kg; $\beta_{f,n,\gamma}$ in Nm^3/h

Table 4.6: Investment alternatives

j	Cap_j^S	C_j^{Cadd}	I_j	j	Cap_j^S	C_j^{Cadd}	I_j	j	Cap_j^S	C_j^{Cadd}	I_j
1	0	0	0	13	10	0.075	316.5	25	10	0.25	514
2	0.5	0	60	14	0.5	0.15	330	26	2	0.5	585
3	2	0	85	15	2	0.15	355	27	4	0.5	616
4	4	0	116	16	4	0.15	386	28	6	0.5	643
5	6	0	143	17	6	0.15	413	29	8	0.5	666
6	8	0	166	18	8	0.15	436	30	10	0.5	689
7	10	0	189	19	10	0.15	459	31	2	0.75	760
8	0.5	0.075	187.5	20	0.5	0.25	385	32	4	0.75	791
9	2	0.075	212.5	21	2	0.25	410	33	6	0.75	818
10	4	0.075	243.5	22	4	0.25	441	34	8	0.75	841
11	6	0.075	270.5	23	6	0.25	468	35	10	0.75	864
12	8	0.075	293.5	24	8	0.25	491				

Cap_j^S in 1000 Nm^3; Cap_j^{Cadd} in 1000 kWh; I_j in 1000 EUR

The market prices of the day-ahead market in the first week of June 2016 are used. In order to model a case with a fixed biogas production rate, similar to the approach of Fichtner and Meyr (2019) is assumed that the biogas production rate represents a steady-state system without the variability of feeding patterns. Therefore, a fixed biogas production rate of 125 Nm^3/h is assumed. Additionally, it is assumed that deviations of this biogas production rate are permitted in a fixed interval $125 - \varepsilon \leq DP_s \leq 125 + \varepsilon$ with $\varepsilon = 5$. This assumption is justified, as there is also a small fluctuation of the biogas rate in reality. Nevertheless, these fluctuations are too small to enable a demand-oriented biogas production, as they are representing the natural fluctuation of the biogas production. This case with an inflexible biogas production rate is used as a benchmark to evaluate the economic benefits of variable substrate feeding.

The results of the first numerical experiments regarding the economic effects of variable substrate feeding are depicted in Figures 4.11 and 4.12. Exemplary operational schedules for the use of feedstock $f = 1$ are depicted in these figures. It was possible to solve the models optimally in less than a minute.

The top graph shows in both figures the considered spot market price data. The second one ((a) Var. feeding PL) represents the feeding schedules/biogas production rates resp. biogas storage filling level/electricity production, if variable substrate feeding with the approximation approach PL is applied. The third one ((b) Var. feeding RS) shows the appropriate results for the RS approach and the fourth part ((c) No var. feeding) consists of the results if no variable feeding is applied.

It is evident that the price curve is characterized by the typical intraday and intraweek seasonalities with a decreasing price at the weekend. In order to be able to produce as much electricity as possible in high price periods (typically during the mid of the day) applying cases a) and b), four blocks of feeding events are realized each from Monday to Thursday in the early morning. After these feedings, no further feedings are necessary. Consequently, the rather small biogas storage is only rarely completely filled. Nevertheless, it is possible to produce electricity on full load in the high price periods with the available biogas.

Without the flexibility out of variable substrate feeding, bigger biogas storage capacities are necessary to reach a demand-oriented electricity production. (Case c)) These bigger storage capacities cause higher investments. Thus, variable substrate feeding is economically beneficial in terms of the necessary investments. Additionally, in Figure 4.12 is depicted, that the flexibility potential is higher if variable substrate feeding is applied. In cases a) and b) more CHP plant starts and thus smaller production times a realized. Thus, the peaks in the spot-market prices are more precisely followed by the production, which leads to a four times higher objective value for the cases with variable substrate feeding than without. The reason is that without variable feeding only the highest price peaks are used for electricity production. Within the remaining times the biogas storage is refilled. In contrast, variable substrate feeding provides the possibility to produce and sell electricity in these times as well, in case there are smaller price peaks. Hence, variable substrate feeding is not only economically beneficial in terms of the long-term investment planning problems, but also in terms of the flexibility potential of the operational schedule.

The results show as well, that for the feeding quantities and the electricity production normally a so-called bang-bang-strategy is used. (Steffen and Weber, 2016) Which means either feeding or electricity production with the maximum quantity or nothing.

In terms of the influence of the two approximation approaches on the optimization can be observed, that the results are quite similar. The operational schedule is, apart from small exceptions, equal, which leads to a relative difference of the objective values of approximately 5 %. This means that the better approximation quality of the RS approach does not lead to a significant change in the optimization results. Thus, in the remainder only the PL approach is applied.

The results of the above experiments have shown that the model can be used directly for the operational scheduling in biogas plants. As a consequence, the model can be beneficial for biogas plant operators who already have a suitable biogas plant configuration and just want to optimize their operational schedule and for those who want

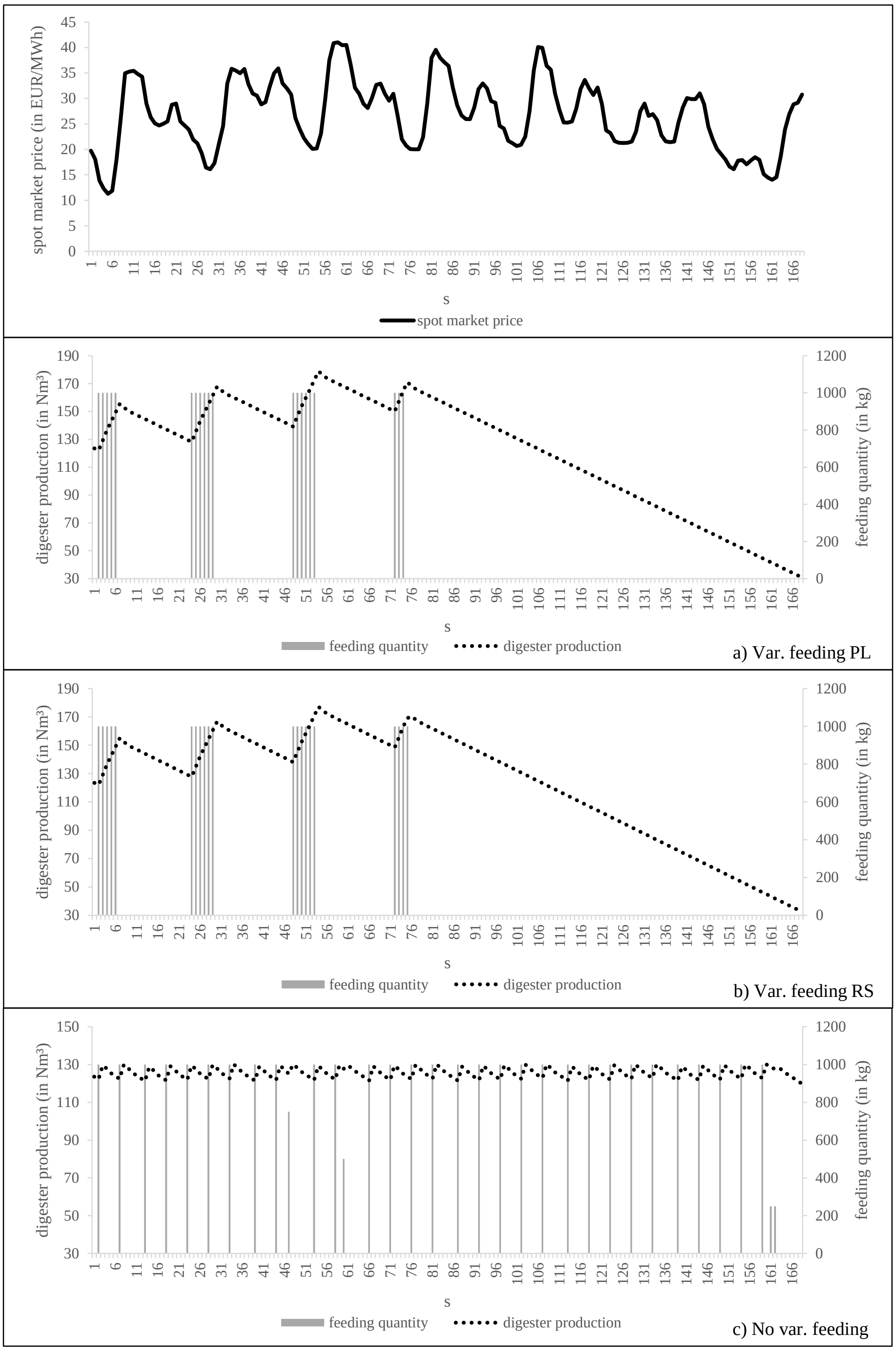

Figure 4.11: Analysis of feeding schedules and biogas production rates

to optimize the plant configuration. Besides, the results of the numerical experiments show the potential economic benefits of variable substrate feeding, independent of the chosen approximation approach.

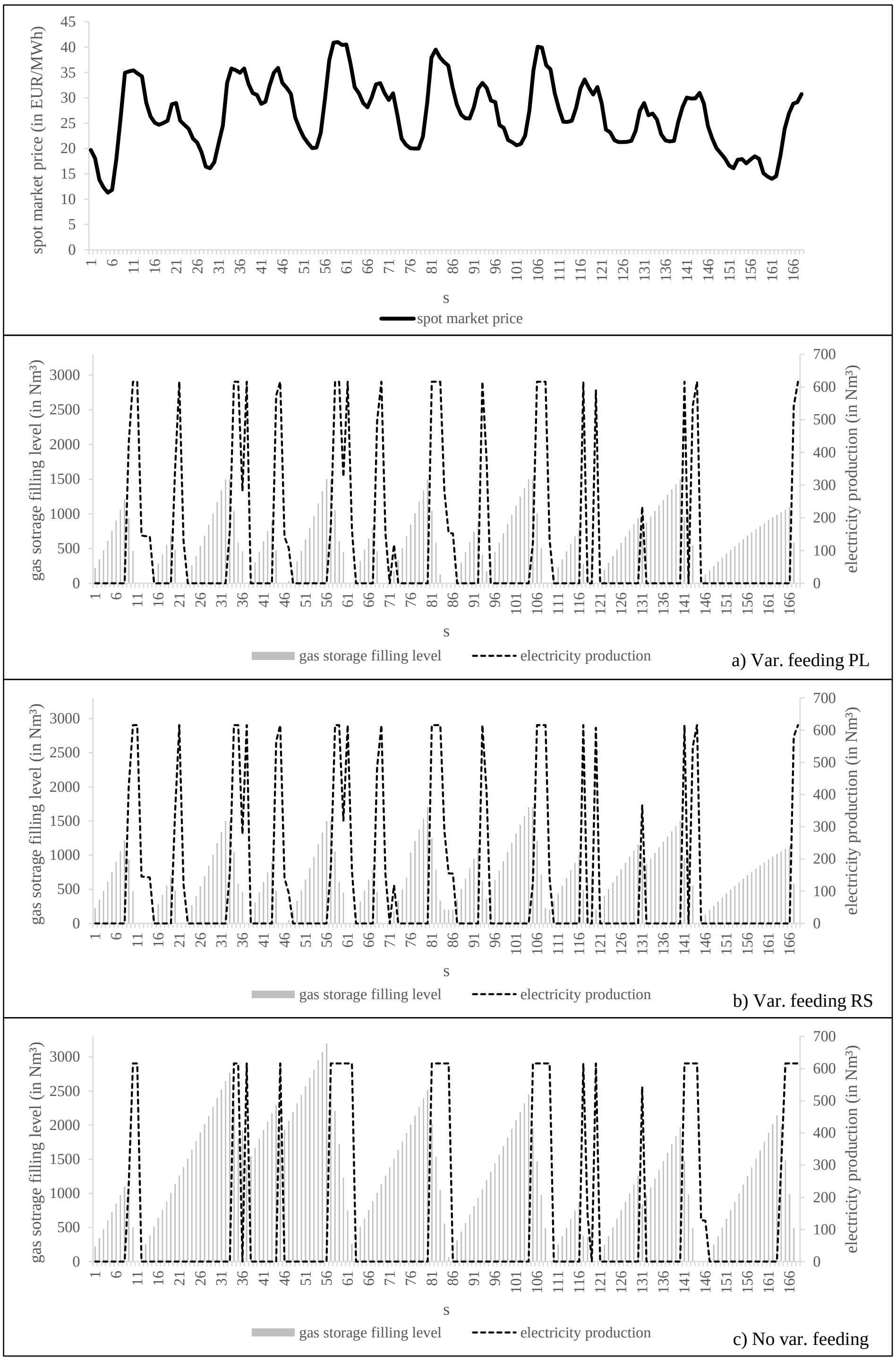

Figure 4.12: Analysis of storage filling levels and electricity production

4.5.3 Effects of different variably fed substrates

The economic potential of variable substrate feeding is discussed in the previous section. In the current section, the economic influence of different variably fed substrates is investigated. Therefore, weekly schedules are generated using different biomass feedstocks and the approximation approach PL. As explained in Section 4.5.1 two real feedstocks (maize/grass silage and ground wheat grain) are used as well as three further fictional ones. The same market data as in the previous experiments is used. In the first step, only one biomass feedstock is separately considered in each calculation run. In further steps, combinations of two, three, and all five feedstocks are implemented.

The resulting objective values of the mentioned numerical experiments are depicted in Table 4.7. Even with all five feedstocks, the models could be optimally solved within a few minutes. It is evident that a combination of several biomass feedstocks can lead to beneficial results. Therefore, the specific combination is crucial. For instance, it is not beneficial to use a combination of feedstocks $f = 1$ and $f = 2$ instead of only using the first one because the results show for the combined case that only the first feedstock is used which results in the same objective value. In contrast, combinations of feedstocks $f = 1$, $f = 2$ and $f = 3$ (resp. $f = 1,2,3$) and $f = 4$ and $f = 5$ are beneficial, as the objective values of the combinations are higher than the cases of separate usage. This behavior is as well explained in Figure 4.13 by showing the resulting feeding quantities within the first ten microperiods for case a) each feedstock $f = 1,2,3$ separately, b) a combination of $f = 1$ and $f = 2$ and c) a combination of $f = 1,2,3$. Decisive for the advantageousness are the characteristics of the combined feedstocks. In part a) each feedstock is used separately, which would end up in three separate charts. In order to conserve space, all three schedules are combined in one chart. The chart shows that if the feedstocks are used separately in different calculation runs, feedings of 1000 kg are chosen for each feedstock in the periods two to six. The charts b) and c) show resulting schedules for the combination of two ($f = 1,2$) and three biomass feedstocks ($f = 1,2,3$). As depicted in Figure 4.13, the characteristics should be complementary to influence the biogas production process at different points in time and generate a more demand-oriented or just in time production. For instance, with regard to the characteristics of feedstocks $f = 1$ and $f = 3$, it is noticeable that the effect of the biogas production rate on a feeding of $f = 1$ is characterized by a more balanced development than in case of $f = 3$. The latter feedstock is characterized by a rapid increase followed by a rapid decrease. Hence, feedstock $f = 1$ is used in times when a slower and more constant reaction of the biogas production rate is needed. In other words for a basic biogas production. In contrast, feedstock $f = 3$ is used if rapid increases are necessary. This conclusion is based on the feedstock characteristics on the one hand and on the input price characteristics on the other hand. Similar correlations can also be found for feedstocks $f = 4$ and $f = 5$. Thus, in general, it can be beneficial to combine feedstocks for a base load production with ones characterized by short reaction times.

Table 4.7: Objective value based on feedstock choice

	objective value in EUR using feedstock f				
each f separately	$f = 1$ 427.95	2 223.59	3 1074.33	4 456.34	5 479.10
comb. of two f	1 & 2 427.95	2 & 3 1074.33	3 & 4 1074.33	4 & 5 542.59	
comb. of three f	1,2,3 1090.52		3,4,5 1074.33		
comb. of five f		1,2,3,4,5 1090.52			

4.5.4 Effects of feedstock prices

Within the previous two Subsections, the operational biogas plant schedules were calculated on the basis of realistic biomass feedstock prices. The used prices are based on data by the FNR, Fachagentur Nachwachsende Rohstoffe e. V. (2009). Nevertheless, prices for biomass are feedstock dependent and can change temporarily or permanently.

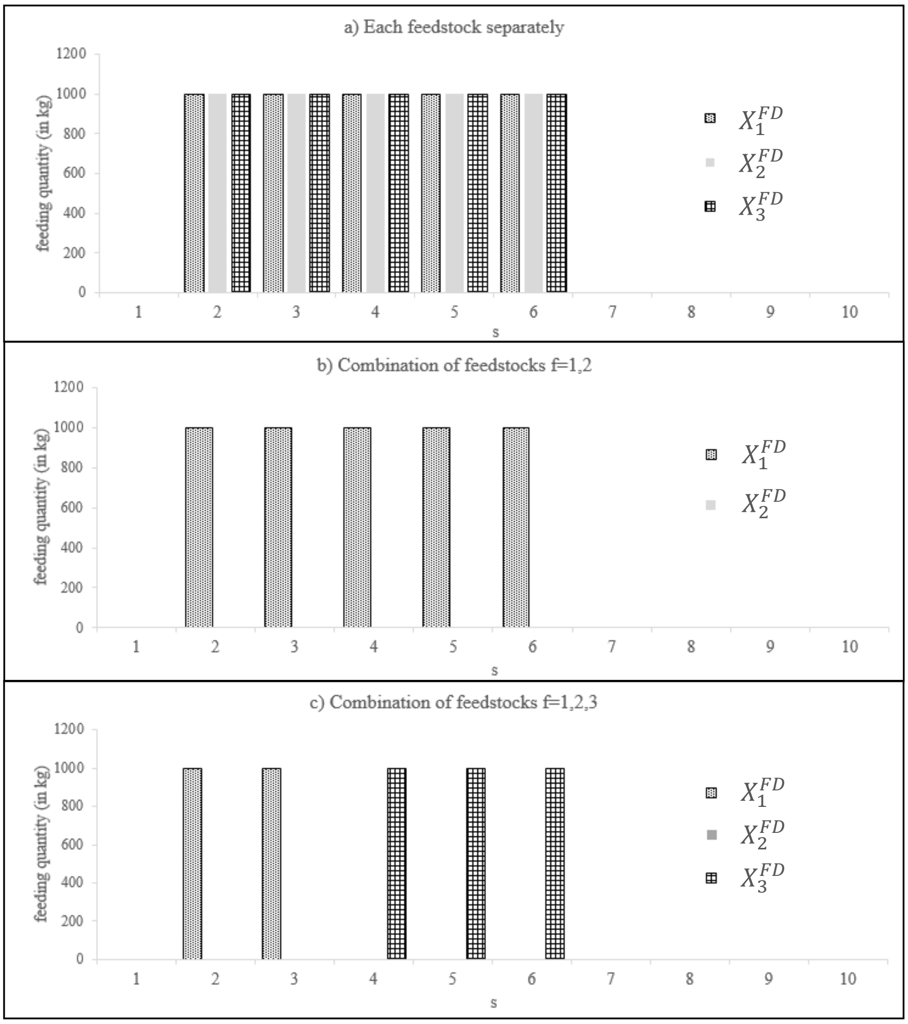

Figure 4.13: Analysis of feeding schedules

Hence, within a strategic planning horizon of five years, the availability and price of biomass feedstocks are subject to uncertainty.

In order to analyze the influence of the biomass feedstock price on the operational optimization and thus the sensitivity of the optimization on the uncertainty, further calculations are generated with manipulated feedstock prices in this Section. On the one hand, biomass feedstock prices could be lower for the biogas plant operators, than considered in Section 4.5.3. This could be the case if only residues are used as substrate. If this is the case, only handling costs for the free of charge available feedstock have to be taken into account. On the other hand, Fichtner and Meyr (2017) have demonstrated, that biomass could be a scarce resource in the future, because various utilization pathways exist. These pathways can lead to a competitive market for biomass, which could end up in rising prices for biomass feedstocks. Additionally, prices for feedstocks can change temporarily due to extreme weather events like storms or drought. Both cases of lower or higher feedstock prices are compared to the realistic feedstock prices used in Sections 4.5.2 and 4.5.3. The results of the generated numerical experiments are depicted in Table 4.8. The calculations are based on feedstock $f = 1$, approximation approach PL and are made for a planning horizon of one week. A halving resp. doubling of the feedstock prices is assumed for the case of low and high prices.

The calculated results show a significant effect of the biomass feedstock price on the optimization. In the case of lower feedstock prices, more feedstock is used to produce more electricity. This results in a significantly higher objective value. In case the biomass feedstock prices are doubled, no effect on feeding and production quantities can be observed. Nevertheless, the operation of the biogas plant would not be beneficial, because the objective value would be negative and thus significantly lower than in the original case. The negative objective value is due to the operating costs of the digester. These costs represent mainly heating costs to keep the temperature in the digester constant. Thus, they are incurred permanently, even if there is no additional feeding. To conclude, the biomass feedstock price is a crucial element of the economic efficiency of a biogas plant in case of variable substrate feeding.

Table 4.8: Effect of feedstock price

	feedstock price		
	low	original	high
objective value (EUR)	1,993.41	427.95	- 2,571.72
$\sum_{f,s} X_{f,s}^{FD}$ (in 1000 kg)	21.25	20.00	20.00
$\sum_s DP_s$ (in 1000 Nm^3)	21.500	20.621	20.621
$\sum_s X_s^{SC}$ (in 1000 Nm^3)	21.588	20.721	20.721

4.5.5 Strategic planning with variable substrate feeding

As explained in Section 4.4, the optimization of the operational schedule of a biogas plant is just one part of the strategic optimization. Within this strategic optimization, the biogas plant design is adjusted. In order to evaluate different investment alternatives and thus different plant designs, the optimized operational schedule is used to simulate future earnings. More precisely, an optimized operational schedule is generated for each investment alternative, which makes this strategic optimization problem hard to solve. Although the major objective of the present work is to optimize only the operational schedule, the conclusions of the previous numerical experiments concerning the operational schedule are tried to be used in the following to reach an optimization of the biogas plant design as well, to show the intended application of the operational schedules and identify potential occuring problems.

Calculation runs with different feedstocks and different solver time limits are executed based on price data from Fichtner and Meyr (2019) (base scenario), with a planning horizon of five years. The executed experiments are simplified in terms of potential uncertainty. On the one hand, in contrast to the approach of Fichtner and Meyr (2019), only one electricity market price scenario is considered. Thus, the spot market price uncertainty is not considered in the following. On the other hand, the uncertainty regarding the biomass feedstock prices, which was analyzed in the previous Section 4.5.4, is not considered in the following, because only currently realistic biomass feedstock prices are assumed. These simplifications were made to focus on the effects of variable substrate feeding.

Within Table 4.9 the results of numerical experiments using the SBPP-VAR model are illustrated. It is recognized that even a problem with only one feedstock type cannot be solved optimally within the chosen time limits for the optimization (18,000 resp. 36,000 sec.). Additionally, the results show that a doubled time limit does not lead to a significant change of the resulting gap of the optimization algorithm of the solver. Moreover, it can be observed that for experiments with three or more feedstocks, no feasible solutions can be found. The results show as well, that for the given experimental design, variable feeding would not be beneficial. (negative upper bound for optimization with feedstock 1) However, this is not a contradiction to the results from Chapter 3, because two different plants with different characteristics are considered. Also, as mentioned in Section 4.5.3 it is beneficial to combine several feedstocks within one biomass digestion process. Thus, strategic optimization should be based on that assumption. Even though such a strategic optimization problem will not be solved regularly, running times with more than 10 hours seem intolerable. Furthermore, these running times are necessary for the calculations of just one price scenario. However, as Fichtner and Meyr (2019) have demonstrated, it is necessary to consider several scenarios in order to model the governmental and market relating uncertainty. Hence, an optimization of the biogas plant design, considering variable substrate feeding and uncertainty would take a tremendous amount of running time. Thus, this approach is not practically applicable. The binary variables concerning the investment decision and the flexibility premium (B_j and $Y_{j,t}$) and the chosen feedstock feeding quantities ($FC_{f,n,s}$) are critical for the optimization process. Especially the latter ones are hard to determine within a full-scale problem size of $F = 5$, $N = 5$, and $S = 43,825$ because in this case, more than one million binary variables have to be determined.

Table 4.9: Solver output SBPP-VAR

feedstock	lower bound*	upper (best) bound*	objective value*	gap in %	time limit in sec.
1	- 1,146.58	- 922.93	-	19.51	18,000
1	- 1,146.58	- 959.35	-	16.33	36,000
1,2,3	-	3,933.71	-	-	18,000
1,2,3	-	3,933.71	-	-	36,000
1,2,3,4,5	-	3,933.71	-	-	18,000
1,2,3,4,5	-	3,933.71	-	-	36,000

*in 1000 EUR

4.6 Summary and outlook

In this paper, it was examined how biogas plants can be adjusted to produce electricity flexibly and on-demand by the consideration of variable substrate feeding. Therefore, the approach of Fichtner and Meyr (2019) is extended. Instead of the objective of adjusting a conventional biogas plant into a type II plant, the aim is to reach a type III plant. Consequently, the biogas production process is influenced by variable substrate feeding. In order to include the resulting volatile biogas production rate into the linear optimization approach by Fichtner and Meyr (2019), in particular in the OBPP and SBPP models, this non-linear production rate is estimated using two approximation approaches. The resulting parameters are implemented in a new decision stage concerning the biomass feeding process into the digester. Similar to the approach of Fichtner and Meyr (2019) the derived deterministic optimization models (OBPP-VAR, SBPP-VAR) are tested using market data of the day-ahead market. Numerical experiments were executed for a fictional but close to reality biogas plant with a rather small capacity, located in southern Germany.

The numerical experiments using the OBPP-VAR model reveal that a variable substrate feeding is sufficient to implement a demand-oriented biogas production in a flexibly operated biogas plant. As a result of this amendment, necessary biogas storage capacities can be reduced. Furthermore, the operational flexibility potential of the biogas plant can be increased by variable substrate feeding. Thus, a more demand-oriented electricity production is possible. Additionally, it can be observed that a combined feeding of several biomass feedstocks in one digestion process can be beneficial to the economic efficiency of the biogas plant. The prices of the chosen feedstocks are as well crucial for the profitability of a biogas plant. Furthermore, it can be concluded that independent of any investment planning problem, the OBPP-VAR model can be applied to optimize the operational biogas plant schedule considering variable substrate feeding, which is a unique second application besides the investment planning problem. Moreover, the optimization model to optimize the biogas plant design strategically is extended to consider variable substrate feeding. Unfortunately, the numerical experiments using this SBPP-VAR model reveal that it is not possible to solve a full-scale example in an acceptable amount of time using a standard solver like Gurobi. Here, the main problem during the optimization process is the determination of a tremendous amount of binary variables concerning the investment, subsidy, and feeding decisions. A potential solution for this problem could be an adjusted modeling of the problem, or developing a solution heuristic. The remaining model should then be easier to solve for standard solvers. However, it has been demonstrated that variable substrate feeding can play a decisive role during the economic optimization of biogas plants. Additionally, the consideration of variable substrate feeding in operational and strategical optimization models with economic focus is achieved, which in particular offers a novel contribution.

Nevertheless, there is potential for further research not only in terms of a heuristic-based solution approach. The decision framework in this paper is characterized by several assumptions. One of these assumptions is that the marketing of the second product heat is not considered in the optimization approach. However, it could be beneficial for biogas plant operators to sell the nascent heat as well. If this is the case, the flexible electricity and thus flexible heat production have to be considered. Therefore, it can be necessary to build heat storage capacities as well because of a missing match of potential customer heat demand and market electricity demand. Additionally, it could be beneficial to consider an adjustment of the digester as well. As mentioned in Section 4.3, several studies exist where the digester design was adjusted before variable substrate feeding was applied. In this course, the assumption that only one investment strategy can be chosen could be neglected to allow several combinations.

Apart from the mentioned extensions, other extensions could cover several energy markets apart from the day-ahead market because a biogas plant operator is allowed to sell the produced electricity on several markets simultaneously. Moreover, in this paper, the biogas plant is examined independently from other market participants. It could be beneficial to examine the biogas plant within a network of other market participants, in a so-called virtual power plant. Instead of extending the already developed models, further research can be necessary for related problems. As explained, the developed models can support the operational as well as the strategic planning in biogas plants. Besides these two planning levels, it could be necessary in further optimization models to optimize mid-term tactical decisions as well. A potential decision in such a model could be the choice of the biomass feedstock type.

4.7 Appendix

Table 4.10: Complete notation OBPP-VAR and SBPP-VAR

Indices	
$d = 1,...,D$	meso periods, days (d) in the planning horizon
$f = 1,...,F$	available biomass feedstock types as substrate
$j = 1,...,J$	discrete investment strategies
$n = 1,...,N$	size categories of feeding quantities of feedstocks
$s = 1,...,S$	microperiods, hours (h) in the planning horizon
$t = 1,...,T$	macroperiods, years (y) in the planning horizon
$\gamma = 0,...,\Gamma$	counter index, last microperiods after a feeding event within the influencing time interval Γ
Sets	
Φ	set of all microperiods
$\Phi_d \subset \Phi$	set of all microperiods in an meso period d
$\Phi_t \subset \Phi$	set of all microperiods in macroperiod t
$\Phi_t^* \in \Phi$	last microperiod in macroperiod t

Parameters	
a	efficiency of CHP plants / produced amount of electricity per Nm^3 biogas in kWh/Nm^3
$\alpha_{f,n,\gamma}$	time depending biogas change of the biogas production rate per kg using a feeding quantity of category n and feedstock f in period γ after a feeding event in Nm^3/kg
Bem^{init}	previously realized output per macroperiod kWh/y
$\beta_{f,n,\gamma}$	produced biogas quantity using feedstock f with feeding quantity of category n in period γ after a feeding event in Nm^3/h
c^E	electricity production costs of a specific biogas plant (variable costs) EUR/kWh
c^F_f	costs for used biomass feedstock f incl. feeding in EUR/kg
c^G	operating costs for digester in EUR/h
Cap^S_j*	installed capacity of a gas storage in investment strategy j in Nm^3
Cap^C	formerly installed CHP plant capacity (maximum amount of electricity produced in one hour) in kWh
Cap^{Cadd}_j*	additionally installed CHP plant capacity in investment strategy j in kWh (maximum amount of electricity produced in one hour) in kWh
dr_s	decreasing depreciation rate per year t in microperiod s $\in \Phi^*_t$
fq_n	discrete feeding quantity input into digester in size category n of a feedstock in kg
i	discounting interest rate per microperiod
I_j	total investment for investment strategy j in EUR
Max^P	sufficiently large number
m_s	market premium in microperiod s in EUR/kWh
p_s	spot market price forecast at the power exchange in the day-ahead market in microperiod s in EUR/kWh
X^{FDmax}	maximum feeding quantity per day in kg
Decision Variables	
$B_j \in \{0,1\}$	decision variable, 1 if investment strategy j is chosen, 0 otherwise
$DP_s \geq 0$	biogas production rate in the digester per microperiod s in Nm^3/h
$FC_{f,n,s} \in \{0,1\}$	decision variable, 1 if feeding quantity in category n of feedstock f in microperiod s is chosen, 0 otherwise
$NPV \geq 0$	objective value
$pr_s \geq 0$	granted flexibility premium in microperiod s in EUR paid once in a year (EUR/y)
$X^{DT}_s \geq 0$	gas flow from digester to the torch in microperiod s in Nm^3
$X^{DS}_s \geq 0$	gas flow from digester to the gas storage in microperiod s in Nm^3
$X^{FD}_{f,s} \geq 0$	flow of biomass feedstock f into the digester in kg in microperiod s
$X^{SC}_s \geq 0$	gas flow from the gas storage to the CHP plants in microperiod s in Nm^3
$X^S_s \geq 0$	gas storage level at the end of microperiod s in Nm^3
$Y_{j,t} \in \{0,1\}$*	decision variable, 1 if the flexibility premium in macroperiod t is requested and if investment strategy j is chosen, 0 otherwise

* In case of the OBPP-VAR, independent of the index j.

Objective function OBPP-VAR:

$$Max \quad \sum_s \underbrace{(p_s + m_s) \cdot a \cdot X_s^{SC}}_{SMP_s} - VEGP_s + \underbrace{pr_s}_{ESP_s} \tag{4.13}$$

$$VEGP_s = \sum_f X_{f,s}^{FD} \cdot c_f^F + c^G + X_s^{SC} \cdot a \cdot c^E \tag{4.14}$$

Constraints OBPP-VAR:

Capacity restrictions

$$X_s^S \leq Cap^S \qquad \forall s \tag{4.15}$$

$$X_s^{SC} \cdot a \leq Cap^C + Cap^{Cadd} \qquad \forall s \tag{4.16}$$

$$\sum_{s \in \Phi_t} a \cdot X_s^{SC} \leq Bem^{init} + (1 - Y_t) \cdot Max^P \qquad \forall t \tag{4.17}$$

$$\sum_{s \in \Phi_t} \frac{a \cdot X_s^{SC}}{|\Phi_t|} \geq \frac{1}{5} \cdot \left(Cap^C + Cap_j^{Cadd}\right) \cdot Y_t \qquad \forall t \tag{4.18}$$

$$pr_s \leq \begin{cases} \left(Cap^C + Cap^{Cadd} - \sum\limits_{s \in \Phi_t} \frac{a \cdot X_s^{SC}}{|\Phi_t|} \cdot 1.1\right) \cdot 130 & \forall s \in \Phi_t^* \quad (4.19a) \\ \left(Cap^C + Cap^{Cadd}\right) \cdot 0.5 \cdot 130 & \forall s \in \Phi_t^* \quad (4.19b) \\ Max^P \cdot Y_t & \forall s \in \Phi_t^* \quad (4.19c) \\ 0 & \forall s \notin \Phi_t^* \quad (4.19d) \end{cases}$$

Mass balance

$$DP_s = X_s^{DS} + X_s^{DT} \qquad \forall s \tag{4.20}$$

$$DP_s = DP_{s-1} + \sum_f \sum_n \sum_\gamma fq_n \cdot FC_{f,n,s-\gamma} \cdot \alpha_{f,n,\gamma} \qquad \forall s^7 \tag{4.21}$$

$$DP_s = \sum_f \sum_n \sum_\gamma FC_{f,n,s-\gamma} \cdot \beta_{f,n,\gamma} \qquad \forall s^8 \tag{4.22}$$

$$X^{FD}_{f,s} = \sum_n fq_n \cdot FC_{f,n,s} \qquad \forall f,s \tag{4.23}$$

$$\sum_f \sum_{s \in \Phi_d} X^{FD}_{f,s} \leq X^{FDmax} \qquad \forall s \tag{4.24}$$

$$\sum_f \sum_n FC_{f,n,s} \leq 1 \qquad \forall s \tag{4.25}$$

$$X^S_s = X^S_{s-1} + X^{DS}_s - X^{SC}_s \qquad \forall s \tag{4.26}$$

Objective function SBPP-VAR:

$$Max \quad NPV = \sum_j \sum_s \frac{(p_s + m_s) \cdot a \cdot X^{SC}_s - VEGP_s + pr_s}{(1+i)^s} - \frac{dr_s}{(1+i)^S} \cdot B_j \cdot I_j \tag{4.27}$$

Additional resp. adjusted constraints SBPP-VAR:

Design configuration

$$\sum_j B_j = 1 \tag{4.28}$$

[7] If PL is applied.
[8] If RS is applied.

$$Y_{j,t} \leq B_j \qquad \forall j,t \quad (4.29)$$

Capacity restrictions

$$X_s^S \leq \sum_j B_j \cdot Cap_j^S \qquad \forall s \quad (4.30)$$

$$X_s^{SC} \cdot a \leq Cap^C + \sum_j B_j \cdot Cap_j^{Cadd} \qquad \forall s \quad (4.31)$$

$$\sum_{s \in \Phi_t} a \cdot X_s^{SC} \leq Bem^{init} + (1 - \sum_j Y_{j,t}) \cdot Max^P \qquad \forall t \quad (4.32)$$

$$\sum_{s \in \Phi_t} \frac{a \cdot X_s^{SC}}{|\Phi_t|} \geq \frac{1}{5} \cdot \sum_j \left(Cap^C + Cap_j^{Cadd} \right) \cdot Y_{j,t} \qquad \forall t \quad (4.33)$$

$$pr_s \leq \begin{cases} \left(Cap^C + \sum_j B_j \cdot Cap_j^{Cadd} - \sum_{s \in \Phi_t} \frac{a \cdot X_s^{SC}}{|\Phi_t|} \cdot 1.1 \right) \cdot 130 & \forall s \in \Phi_t^* \quad (4.34a) \\ \left(Cap^C + \sum_j B_j \cdot Cap_j^{Cadd} \right) \cdot 0.5 \cdot 130 & \forall s \in \Phi_t^* \quad (4.34b) \\ \sum_j Max^P \cdot Y_{j,t} & \forall s \in \Phi_t^* \quad (4.34c) \\ 0 & \forall s \notin \Phi_t^* \quad (4.34d) \end{cases}$$

Bibliography

Ahmed, S., Kazda, M., 2017. Characteristics of on-demand biogas production by using sugar beet silage. Anaerobe 46, 114–121. doi:10.1016/j.anaerobe.2017.04.016.

Almgren, H., 1999. Start–up of advanced manufacturing systems – a case study. Integrated Manufacturing Systems 10, 126–136. doi:10.1108/09576069910264385.

Barchmann, T., Mauky, E., Dotzauer, M., Stur, M., Weinrich, S., Jacobi, F., 2016. Erweiterung der Flexibilität von Biogasanlagen – Substratmanagement, Fahrplansynthese und ökonomische Bewertung. Landtechnik Agricultural Engineering 71, 233–251.

Birge, J.R., Louveaux, F., 1997. Introduction to stochastic programming. Springer series in operations research, Springer, New York.

Bradley, S.P., Hax, A.C., Magnanti, T.L., 1992. Applied mathematical programming. 19 ed., Addison-Wesley, Reading, Mass.

Deutsche Bundesbank, 2017. Abzinsungszinssätze gemäß § 253 Abs. 2 HGB / 7 Jahresdurchschnitt. URL: https://www.bundesbank.de/Redaktion/DE/Downloads/Statistiken/Geld_Und_Kapitalmaerkte/Zinssaetze_Renditen/abzinsungszinssaetze.pdf;jsessionid=0000GZtDCJRS0sdfohAZEF49ywT:-1?__blob=publicationFile. accessed 2018-07-05.

Domschke, W., Drexl, A., Klein, R., Scholl, A., 2015. Einführung in Operations Research. 9 ed., Springer Berlin Heidelberg, Berlin, Heidelberg. doi:10.1007/978-3-662-48216-2.

Ertem, F.C., Martínez-Blanco, J., Finkbeiner, M., Neubauer, P., Junne, S., 2016. Life cycle assessment of flexibly fed biogas processes for an improved demand-oriented biogas supply. Bioresource technology 219, 536–544. doi:10.1016/j.biortech.2016.07.123.

Feng, L., Ward, A.J., Guixé, P.G., Moset, V., Møller, H.B., 2018. Flexible biogas production by pulse feeding maize silage or briquetted meadow grass into continuous stirred tank reactors. Biosystems Engineering 174, 239–248. doi:10.1016/j.biosystemseng.2018.07.013.

Fichtner, S., Meyr, H., 2017. Strategic Supply Chain Planning in Biomass-Based Industries: A Literature Review of Quantitative Models, in: Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), Knowledge-driven developments in the bioeconomy. Springer Verlag, Cham. Economic complexity and evolution, pp. 259–291.

Fichtner, S., Meyr, H., 2019. Biogas plant optimization by increasing its flexibility considering uncertain revenues. Hohenheim Discussion Papers in Business, Economics and Social Sciences 07, 1–48. Stuttgart.

Fjällström, S., Säfsten, K., Harlin, U., Stahre, J., 2009. Information enabling production ramp–up. Journal of Manufacturing Technology Management 20, 178–196. doi:10.1108/17410380910929619.

FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2009. Biogas-Messprogramm II: 61 Biogasanlagen im Vergleich. Nachwachsende-rohstoffe.de. 1 ed., FNR, Gülzow.

FNR, Fachagentur Nachwachsende Rohstoffe e. V., 2017. Faustzahlen. URL: https://biogas.fnr.de/daten-und-fakten/faustzahlen/. accessed 2017-11-07.

Glock, C.H., Jaber, M.Y., Zolfaghari, S., 2012. Production planning for a ramp-up process with learning in production and growth in demand. International Journal of Production Research 50, 5707–5718. doi:10.1080/00207543.2011.616549.

Grim, J., Nilsson, D., Hansson, P.A., Nordberg, Å., 2015. Demand-Orientated Power Production from Biogas: Modeling and Simulations under Swedish Conditions. Energy & Fuels 29, 4066–4075. doi:10.1021/ef502778u.

Hahn, H., Krautkremer, B., Hartmann, K., Wachendorf, M., 2014. Review of concepts for a demand-driven biogas supply for flexible power generation. Renewable and Sustainable Energy Reviews 29, 383–393. doi:10.1016/j.rser.2013.08.085.

Helber, S., Sahling, F., Schimmelpfeng, K., 2013. Dynamic capacitated lot sizing with random demand and dynamic safety stocks. OR Spectrum 35, 75–105. doi:10.1007/s00291-012-0283-6.

Kressner, A., 2017. Modelle und Lösungsverfahren für die Hauptoperationsplanung bei unsicheren Operationsdauern. Ph.D. thesis. Universität Hohenheim. Stuttgart.

Kuratorium für Technik und Bauwesen in der Landwirtschaft e. V. (Ed.), 2018. Faustzahlen für die Landwirtschaft. KTBL, Darmstadt.

Lemmer, A., Krümpel, J., 2017. Demand-driven biogas production in anaerobic filters. Applied Energy 185, 885–894. doi:10.1016/j.apenergy.2016.10.073.

Lin, M.H., Carlsson, J.G., Ge, D., Shi, J., Tsai, J.F., 2013. A Review of Piecewise Linearization Methods. Mathematical Problems in Engineering 2013, 1–8. doi:10.1155/2013/101376.

Linke, B., Rodríguez-Abalde, Á., Jost, C., Krieg, A., 2015. Performance of a novel two-phase continuously fed leach bed reactor for demand-based biogas production from maize silage. Bioresource technology 177, 34–40. doi:10.1016/j.biortech.2014.11.070.

Matta, A., Tomasella, M., Valente, A., 2007. Impact of ramp-up on the optimal capacity-related reconfiguration policy. International Journal of Flexible Manufacturing Systems 19, 173–194. doi:10.1007/s10696-007-9023-7.

Mauky, E., Jacobi, H.F., Liebetrau, J., Nelles, M., 2015. Flexible biogas production for demand-driven energy supply – Feeding strategies and types of substrates. Bioresource technology 178, 262–269. doi:10.1016/j.biortech.2014.08.123.

Mauky, E., Weinrich, S., Jacobi, H.F., Nägele, H.J., Liebetrau, J., Nelles, M., 2017. Demand-driven biogas production by flexible feeding in full-scale - Process stability and flexibility potentials. Anaerobe 46, 86–95. doi:10.1016/j.anaerobe.2017.03.010.

Mauky, E., Weinrich, S., Nägele, H.J., Jacobi, H.F., Liebetrau, J., Nelles, M., 2016. Model Predictive Control for Demand-Driven Biogas Production in Full Scale. Chemical Engineering & Technology 39, 652–664. doi:10.1002/ceat.201500412.

Popp, W., 1983. Strategische Planung für eine multinationale Unternehmung mit gemischt-ganzzahliger Programmierung. Operations-Research-Spektrum 5, 45–57. doi:10.1007/BF01720287.

Riemann, B., 1867. Ueber die Darstellbarkeit einer Function durch eine trigonometrische Reihe. Dieterich, Göttingen. doi:10.3931/e-rara-49760.

Scarlat, N., Dallemand, J.F., Fahl, F., 2018. Biogas: Developments and perspectives in Europe. Renewable Energy 129, 457–472. doi:10.1016/j.renene.2018.03.006.

Schmidt, L.D., 1998. The engineering of chemical reactions. Topics in chemical engineering, Oxford University Press, New York.

Steffen, B., Weber, C., 2016. Optimal operation of pumped-hydro storage plants with continuous time-varying power prices. European Journal of Operational Research 252, 308–321. doi:10.1016/j.ejor.2016.01.005.

Terboven, C., Ramm, P., Herrmann, C., 2017. Demand-driven biogas production from sugar beet silage in a novel fixed bed disc reactor under mesophilic and thermophilic conditions. Bioresource technology 241, 582–592. doi:10.1016/j.biortech.2017.05.150.

5 Summary and outlook

The present thesis focuses on strategic network planning in biomass-based supply chains. The intention was to generate a significant contribution in the field of strategic optimization in biomass-based supply chains. The focus was on problems arising in practical applications. Particularly, the thesis is structured into three main parts: contribution of an extensive literature review regarding strategic supply chain planning in biomass-based industries, development of an optimization approach for a specific strategic planning problem in biomass-based industries with practical significance and the extension of this approach concerning further characteristics. In particular, within the second part of the thesis, an innovative strategic optimization in biogas plants concerning their flexibility and thus the main contribution of the entire thesis – the development of an innovative practically applicable optimization approach considering technical and legal circumstances – is realized. The developed models are extended in the third part regarding variable substrate feeding. The following Section describes the results in detail. Additionally, further research topics are discussed in Section 5.2.

5.1 Summary

In order to ensure a structured processing of the results of this thesis, the research objectives, formulated in Section 1.2, are picked up again.

> ***Research objective 1:***
>
> *Structured analysis of the landscape of strategic long-term supply chain planning problems within bioeconomy.*
>
> ***Sub-objective 1.1:***
>
> *Clustering of sub-problems in branches and identification of specific characteristics.*
>
> ***Sub-objective 1.2:***
>
> *Identification of research gaps regarding strategic planning in biomass-based supply chains.*

In the literature review of strategic supply chain planning in biomass-based industries in Chapter 2, it can be stated that biomass utilization pathways, which can be transferred into biomass-based supply chains, can be grouped according to their final products. Four groups – fuel, fibre, food, flowers & fun – are identified. For these groups, characteristic elements and the current state of research are examined. As results of and conclusions from the analysis, some characteristics of biomass-based supply chains, some trends of current research on the strategic planning of biomass-based supply chains and some research gaps have been identified. On the one hand, it is noticeable that the research effort on the strategic planning of supply chains producing fuels and rather "innovative" fibres from biomass seems to be decreasing. This is caused by a decrease in research on biofuel production. Overall, peak efforts were recorded in the years 2011 and 2012, with research thereby mainly focusing on plants-based biomass. On the other hand, the following characteristics of biomass-based supply chains have been identified: Biomass-based supply chains are inter-organizational and characterized by a great heterogeneity of parties involved. This heterogeneity should be tackled by employing inter-organizational cooperation and intra-organizational coordination. However, most of the analyzed models assume an intra-organizational view with a central, omniscient and omnipotent planner. High uncertainty concerning the biomass supply is another important characteristic of biomass-based supply chains, which is considered by some models. High transportation costs of unprocessed biomass, caused by its high water content and low energy density, are a further characteristic. Because of them, decisions on locations for pre-processing and conversion facilities are crucial and thus considered by most of the analyzed models. Research gaps are identified concerning optimization models, which take inter-organizational aspects of biomass-based supply chains into account, in order to make them profitable on their own. These models need to be brought as close to reality as possible. (Fichtner and Meyr, 2017)

Research objective 2:

Strategic optimization of biogas plants considering increased flexibility.

Sub-objective 2.1:

Structured analysis of technical and legal circumstances.

Sub-objective 2.2:

Analysis and forecasting of energy spot market prices.

Sub-objective 2.3:

Development of a robust optimization approach.

In Chapter 3 one specific planning problem out of the identified research gaps is tackled. The planning problem is part of the utilization pathway “fuel” and dealing with the strategic optimization of biogas plants. The main problem is to adjust the biogas plant design by installing biogas storage capacities, in order to be able to produce electricity flexibly and on-demand. Therefore, several flexible biogas plant configurations are identified, which all cause investments. In order to evaluate these investments, a multi-stage optimization approach is developed, which takes price uncertainty at the energy spot market, using price scenarios, into account. To model relevant market developments in the future using scenarios, it was discovered that it is necessary to model trends and seasonal characteristics of the spot market prices. The uncertainty of the governmental subsidies determine the choice of doing an investment or not as well. Thus, the investment decision depends not only on the development of the spot market prices but also on the governmental subsidies, namely the flexibility and market premium. The main part of the optimization approach is built up by the operational and strategic optimization models OBPP and SBPP. The decision rules of Hurwizc and the Maximin rule are used to generate a robust solution for a risk-averse decision-maker. Numerical experiments have revealed that the uncertainty of the flexibility premium determines the choice of doing an investment or not. If the flexibility premium is granted, a high investment is chosen in any case of spot market price developments. If not, a small investment is chosen. To conclude, the developed approach gives decision support to a risk-averse biogas plant operator who decides about choosing direct marketing, producing electricity demand-driven and therefore an adjustment of the biogas plant design. All governmental requirements and regulations of the German energy market are modeled and the possible sources of revenues are distinguished. As well, the resulting payouts are considered. Hence, the long-term investment decision can be supported by optimizing an operational schedule. (Fichtner and Meyr, 2019)

Research objective 3:

Economic optimization of biogas plants considering variable substrate feeding.

Sub-objective 3.1:

Linear approximation of non-linear biogas production rates.

Sub-objective 3.2:

Extension of the developed optimization approach regarding variable substrate feeding.

The previously developed optimization approach concerning the strategic optimization of biogas plants considering their flexibility is extended in Chapter 4. The main objective of this last part of the thesis is to consider a demand-oriented biogas production in the digester by using variable substrate feeding. Therefore, the characteristics of variable biogas production rates are analyzed. As the resulting biogas production rates follow a non-linear demand pattern, these rates are approximated using two approximation approaches - piecewise linearization and Rieman sums. Afterwards, the variable biogas production rate is included in the developed optimization models OBPP-VAR and SBPP-VAR. For an operational biogas plant schedule, the results of a numerical example show that variable substrate feeding can have a positive economic effect on demand-oriented plant operation. As a result of this amendment, necessary biogas storage capacities can be reduced. Furthermore, the operational flexibility potential of the biogas plant can be increased by variable substrate feeding. Thus, a more demand-oriented electricity production is possible. Additionally, it can be observed that a combined feeding of several biomass feedstocks in one digestion process can be beneficial to the economic efficiency of the biogas plant. The prices of the chosen feedstocks are crucial as well for the profitability of a biogas plant. Furthermore, it can be concluded that independent of any investment planning problem, the OBPP-VAR model can be applied to optimize the operational biogas plant schedule considering variable substrate feeding, which is a unique second application besides the modeled but not yet optimally solved investment planning problem. Moreover, the optimization model to optimize the biogas plant design strategically is extended to consider variable substrate feeding. Nevertheless, the numerical experiments using this SBPP-VAR model reveal that it is not possible to solve a full-scale example in an acceptable amount of time using a standard solver like Gurobi. Here, the main problem during the optimization process is the determination of a tremendous amount of binary variables concerning the investment, subsidy and feeding decisions. However, it has been demonstrated that variable substrate feeding can play a decisive role during the economic optimization of biogas plants in a short-term, operational planning horizon. Additionally, the consideration of variable substrate feeding in operational and strategic operations research models is achieved, which in particular offers a novel contribution.

What all optimization models of Chapters 3 and 4 have in common is the extraordinary high granularity - on an hourly basis. This high granularity within the optimization of the operational biogas plant schedule is necessary, because of the identified sources of uncertainty as well as the technical, legal and market-based circumstances. An optimization and not only a simulation of the operational schedule is needed, because the scheduling includes revenue-effective decisions, which are crucial for the strategic investment decision. This high level of detail within the models, combined with the strategic, long-term planning horizon, makes the solvability of the models considerably more difficult.

5.2 Outlook

Based on the results of our analysis and numerical studies, several opportunities for further research are identified. Within the literature review in Chapter 2 it is concluded that future research should take inter-organizational aspects of supply chain management into account. Apart from the solved strategic planning problem in biogas plants (Chapters 3 and 4), several other biomass-based supply chains should be optimized to become profitable on their own, i.e., without governmental subsidies, to be able to compete with their fossil-based counterparts. Therefore, the existing intra-organizational models with a central planner could be used as a basis and benchmark. Important is that the legal circumstances in the bioeconomy are highly volatile. Hence, developed models need to be permanently adapted to the new surrounding constraints. This probably makes future research on existing approaches necessary as well.

Moreover, there are further opportunities for future research, with regard to the tackled strategic planning problem in biogas plants. It is mentioned that a more detailed consideration of market- and subsidy-related uncertainties by an application of stochastic optimization can be used to derive an optimal solution directly because then all scenarios can be considered simultaneously. However, more effort in terms of computation time is necessary to derive an optimal solution for a stochastic model than for a deterministic one. Besides the use of stochastic variables, the risk attitude of the decision-maker could be covered more precisely using the Conditional Value at Risk. Additionally, the robustness of the solution could be ensured using a robustness function.

Furthermore, assumptions of the developed optimization approach could be changed to improve and adapt the generated solution. One adaption regarding the variable biogas production rate is made in Chapter 4. A second beneficial extension could be that pre-defined combinations of single biogas storages and single CHP plant capacity extensions are substituted by the possibility to combine several CHP plants and biogas storages. This could lead to further flexibility potentials. In addition, the part of the approach concerning optimizing the operational schedule could be modeled more precisely by considering more detailed constraints. For instance, Butemann and Schimmelpfeng (2019) consider wear and tear in the optimization of the operational schedule. It could be beneficial to include this aspect into the strategic planning problem by a combination of the two operational optimization models.

Besides the adaption of made assumptions, further markets could be included in the optimization approach. Currently, the approach is based on direct marketing on the day-ahead market. As it is possible to sell the produced electricity simultaneously on several spot markets, these markets could be considered as well. In order to include the opportunity of selling on several markets, further price data is necessary to evaluate the profitability of different markets. Hence, it would be necessary to repeat the descriptive spot market price analysis for all other markets. Additionally, the optimization models have to be adapted regarding the requirements of the added markets. For instance, electricity on the intraday market is sold in time intervals of 15 minutes. Thus, another time index, resp. a changed definition of the used indices would be necessary. Besides these additional markets for the product electricity, the marketing of the nascent product heat could be beneficial as well. This heat is generated during the combustion process of the biogas in the CHP plant. If this is the case, the flexible electricity and thus flexible heat production have to be considered. Therefore, it can be necessary to build heat storage capacities as well, because of a missing match of potential customer heat demand and market electricity demand. Additionally, it could be beneficial to consider an adjustment of the digester as well. As mentioned in Section 4.3, several studies exist, where the digester design is adjusted before variable substrate feeding is applied.

As mentioned in the part of the numerical experiments in Chapter 4, the strategic optimization model considering increased flexibility and variable substrate feeding cannot be solved in a reasonable amount of time. Thus, several approaches to generate an optimal (or best possible) solution are discussed. As part of future research, it could be beneficial to adjust the implementation and/or the modeling to decrease the number of binary variables or to (partly) substitute the standard solver Gurobi by a heuristical algorithm. One of several possible approaches could be an adaption of the fix-and-optimize heuristic, developed by Sahling (2010).

Instead of extending the already developed models, further research could be beneficial for related problems. As explained, the developed models can support the operational as well as the strategic planning in biogas plants. Besides these two planning levels, it could be necessary for further optimization models to optimize mid-term tactical decisions as well. A potential decision in such a model could be the choice of the biomass feedstock type. Moreover, in this thesis, the biogas plant is examined independently from other power plants, power storages or power consumers. It could be beneficial to examine the biogas plant design within a network of other market participants in the future – as part of a so-called virtual power plant (VPP). Here, other flexibility options, for instance, pumped-storage power plants, are considered besides the biogas plant, which can lead to other design decisions. One of several possible approaches could be to include the developed multi-stage strategic biogas plant optimization approach in the approach by Lauven (2019), to optimize the biogas plant as part of a VPP.

Bibliography

Butemann, H., Schimmelpfeng, K., 2019. Long-term electricity production planning of a flexible biogas plant considering wear and tear. Journal of Business Economics 15. doi:10.1007/s11573-019-00937-2.

Fichtner, S., Meyr, H., 2017. Strategic Supply Chain Planning in Biomass-Based Industries: A Literature Review of Quantitative Models, in: Dabbert, S., Lewandowski, I., Weiss, J., Pyka, A. (Eds.), Knowledge-driven developments in the bioeconomy. Springer Verlag, Cham. Economic complexity and evolution, pp. 259–291.

Fichtner, S., Meyr, H., 2019. Biogas plant optimization by increasing its flexibility considering uncertain revenues. Hohenheim Discussion Papers in Business, Economics and Social Sciences 07, 1–48. Stuttgart.

Lauven, L.P., 2019. Two-Stage Unit Commitment Modeling for Virtual Power Plants, in: Fortz, B., Labbé, M. (Eds.), Operations Research Proceedings 2018, Springer International Publishing, Cham. pp. 167–173.

Sahling, F., 2010. Mehrstufige Losgrößenplanung bei Kapazitätsrestriktionen. Gabler, Wiesbaden. doi:10.1007/978-3-8349-8708-2.

Curriculum Vitae

Stephan Fichtner

Persönliche Angaben	
Geburtsort	Backnang, Baden-Württemberg, Deutschland
Staatsangehörigkeit	Deutsch
Akademische Ausbildung	
06/2015 - Heute	Promotionsstudiengang Wirtschaftswissenschaften angestrebter Abschluss: Dr. oec. Lehrstuhl für Supply Chain Management Prof. Dr. Herbert Meyr Universität Hohenheim, Deutschland
10/2012 - 09/2014	Studium in Management Abschluss: Master of Science Studienschwerpunkte: Interorganizational Management & Performance, Umweltmanagement Universität Hohenheim, Deutschland
10/2009 - 09/2012	Studium Wirtschaftswissenschaften Abschluss: Bachelor of Science Studienschwerpunkte: Supply Chain Management, Interne Managementfunktionen, Soziologie Universität Hohenheim, Deutschland
06/2009	Abitur Bildungszentrum Weissacher Tal Weissach im Tal, Deutschland
Berufliche Tätigkeiten	
Akademisch	Wissenschaftlicher Mitarbeiter Hochschuldozent in den Bereichen Supply Chain Managenent, Logistik, Beschaffung und Produktion, Operations Research, Projektmanagement, Operations Management
Nicht-akademisch	Praktische Erfahrungen in der Maschinenbau- bzw. Luft- und Raumfahrtindustrie Bereiche: Einkauf, Logistik, Unternehmensentwicklung