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Optimization of Investments for Strategic Process Integration and Pulp Mill Biorefinery Projects under Uncertainty

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Heat and Power Technology
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CHALMERS UNIVERSITY OF TECHNOLOGY
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ABSTRACT

Energy-intensive industrial plants operate in a changing, uncertain environment. Long-term changes are expected in energy prices, political regulations and technology development. Pulp and paper companies, like many other industries, are under strong pressure to respond to these changes. At the same time, there are many opportunities connected to the changing conditions for these companies thanks to their control and experience of the wood biomass resource. These opportunities include the production of green electricity, wood fuels, and district heating, as well as emerging biorefinery products such as green transportation fuels, chemicals and biomaterials. However, uncertainty regarding future energy market conditions and the development of emerging biorefinery processes inevitably makes the decision between competing technologies difficult.

Process integration is a requirement for the successful implementation of pulp mill biorefinery concepts. This thesis presents a systematic methodology for the optimization of investments in process integration under energy market and technology uncertainty with applications to strategic pulp mill biorefinery projects. The methodology is based on multistage stochastic programming and allows for investments at multiple points in time. Decisions are modelled to be made before knowing the outcome of the future energy market development; thereby incorporating the energy market uncertainties explicitly in the optimization model. The investment plan that maximizes the expected net present value can then be obtained given the assumed probabilities of the different energy market developments. Scenarios are also proposed for the analysis of different investment cost developments of emerging pulp mill biorefinery technologies.

As illustrated in this thesis, change, flexibility and lock-in effects are strongly connected. The proposed models capture, among other things, the value of the flexibility needed to avoid future lock-in situations; a value which, as shown, can be significant. The thesis also discusses the flexibility lost due to long lead times. The case studies show that for many mills there is traditional technology available that should be invested in today. Some of today's investment opportunities will, however, lead to lock-in effects if implemented. It is therefore important to evaluate both current and future investment projects in the same optimization model, thereby enabling the identification of the investments that can be cost-effectively implemented today while retaining the opportunity for more far-reaching, future projects. The methodology proposed in this thesis, which is used to identify the investments that are optimal under uncertainty, can thus yield an improved understanding of how investments made today affect later investment opportunities in a long-term perspective.

Keywords: Process integration, biorefinery, pulp and paper industry, stochastic programming, investment planning, scenario-based modelling.

Appended papers

This thesis is based on the work described in the following papers:

I. An optimization methodology for identifying robust process integration investments under uncertainty
Svensson E, Berntsson T, Strömberg A-B and Patriksson M (2009)
Energy Policy, 37(2): 680–685

II. Benefits of using an optimization methodology for identifying robust process integration investments under uncertainty – A pulp mill example
Svensson E, Berntsson T and Strömberg A-B (2009)
Energy Policy, 37(3): 813–824

III. A model for optimization of process integration investments under uncertainty
Svensson E, Strömberg A-B and Patriksson M (2011)
Energy, 36(5): 2733–2746

IV. Using optimization under uncertainty to study different aspects of process integration investment decisions – The example of lock-in effects
Svensson E and Berntsson T (2010)
In Proceedings of ECOS – the 23rd International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, Lausanne, Switzerland, 14–17 June 2010, Vol. I, pp. 233–240

V. Planning future investments in emerging technologies for pulp mills considering different scenarios for their investment cost development
Svensson E and Berntsson T (2011)
Energy, 36(11): 6508–6519

VI. The effect of long lead times for planning of energy efficiency and biorefinery technologies at a pulp mill
Svensson E and Berntsson T
Accepted for publication in Renewable Energy
(A similar version of this paper is available in Proceedings of WREC – the World Renewable Energy Congress, Linköping, Sweden, 8–13 May 2011, Vol. 7, pp. 1481–1488)

VII. Strategic investment planning for process integration under changing conditions
Svensson E, Berntsson T and Strömberg A-B
Submitted to Energy

Co-authorship statement

Elin Svensson is the main author of all appended papers. Professor Thore Berntsson supervised the work in Papers I–II and IV–VII. Associate professor Ann-Brith Strömberg co-supervised the work in Papers I–III and VII. Professor Michael Patriksson supervised the work in Paper III and co-supervised the work in Paper I.

Related work not included in this thesis

- A scenario-based stochastic programming model for the optimization of process integration opportunities in a pulp mill
  Svensson E, Strömberg A-B and Patriksson M (2008)
  Department of Mathematical Sciences at Chalmers University of Technology and University of Gothenburg, ISSN 1652-9715, no 2008:29

- Economy and C_{O2} emissions trade-off: A systematic approach for optimizing investments in process integration measures under uncertainty
  Svensson E and Berntsson T (2008)
  Applied Thermal Engineering, 30(1): 23–29
  (A more extensive version of this paper is available in Proceedings of PRES – the 11th Conference on Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reductions, Prague, Czech Republic,24–28 August 2008)

Other work by the author not included in this thesis

- Pinch analysis of a partly integrated pulp and paper mill
  Svensson E and Harvey S (2011)
  In Proceedings of WREC – the World Renewable Energy Congress, Linköping, Sweden, 8–13 May 2011, Vol. 7, pp. 1521–1528

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1 Introduction

Energy-intensive industrial plants operate in a changing and uncertain environment. Following the increased attention to environmental issues and the stronger global competition, long-term changes are expected in energy market conditions, political regulations and technological development. The rate and magnitude of these changes are, however, highly uncertain. The pulp and paper industry, which is both energy-intensive and in control of large shares of the renewable biomass resource, is clearly under strong pressure to respond to these changes. However, owing to their control over the wood resource and their experience of handling large quantities of biomass, pulp and paper mills have many opportunities connected to these changes if they manage to respond in a successful way. These opportunities include not only traditional products such as green electricity, wood fuels, and district heating, but also a transformation of the pulp mill into a forest biorefinery[1] with the production of green transportation fuels, new specialty chemicals and biomaterials, in addition to pulp and paper. Process integration for the efficient use of energy is a requirement for the successful implementation of these technologies and is also the starting point of this work.

Today, there is great uncertainty regarding the future price levels of both traditional energy and pulp products and non-traditional biorefinery products. Furthermore, many of the emerging energy and biorefinery technologies under consideration today within the pulp and paper industry are not yet commercial. It is therefore very difficult for a company to know which technologies and products the mill should plan for. Nevertheless, the mills are already under pressure to start increasing their energy efficiency in order to reduce fuel demand and/or to produce more traditional energy products such as electricity and district heating. With this ambition, it is, however, as shown in this thesis, important to avoid a future lock-in situation in which it is impossible or drastically more expensive to implement more far-reaching projects of, for example, different biorefinery concepts.

Strategies for the implementation of process integration and biorefinery processes in pulp mills should therefore consider both current and future investment opportunities and the uncertainties that affect the investment decisions. An investment optimization model that properly includes the changing and uncertain parameters is a valuable tool for the identification of flexible and robust investment decisions and for the analysis of possible lock-in effects.

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[1] The concept of a pulp mill biorefinery is defined in Chapter 4.

1.1 Aim

The aim of this thesis is to propose a methodology for the optimization of strategic process integration investments under uncertainty. The pulp and paper industry with its opportunities for biorefinery implementation is in special focus.

Use of the developed methodology should yield a better understanding of risks and opportunities, flexibility and robustness related to strategic investment decisions, thereby yielding an improved basis for decision-making regarding such investments. The methodology should also illustrate the importance of making the right series of decisions in a long-term strategic perspective.

A more elaborate description of the objectives can be found in Chapter 3.

1.2 Papers

The thesis is based on seven papers. Below, brief descriptions of the papers are presented.

In **Papers I and II** a methodology for the optimization of process integration investments under energy market uncertainty is proposed and illustrated. **Paper I** presents the five-step optimization methodology based on a multistage stochastic programming approach and **Paper II** presents a case study in which the methodology is used. The underlying mathematical model formulation specific for the case study was presented in a separate report which is not included in this thesis [1].

The mathematical formulation of a more general form of the optimization model is described in **Paper III**. **Paper III** also includes a simplified example.

Paper IV presents a case study in which the methodology described in **Papers I and III** is used. The paper illustrates how the methodology can be used to study a certain factor that influences the investment decision. In the example presented in **Paper IV**, the risk of lock-in effects due to a long district heating contract is studied.

In **Paper V** an approach to the modelling of uncertain investment costs is proposed. Uncertainty in investment costs is assumed for emerging technologies which are not yet available on a commercial scale. The scenarios proposed represent uncertainty with regard to both the timing of the market introduction of these technologies and their future cost levels. **Paper VI** builds on the framework developed in **Paper V** and proposes an approach to studying the effects of long lead times between the first decision to start planning for an investment and the actual implementation.

The last paper of the thesis, **Paper VII**, summarizes some important lessons learnt during the work on the earlier papers. **Paper VII** illustrates the importance of modelling how investment decisions are affected by conditions that change over time. As a consequence, also future investment opportunities should be considered in the model. As shown in the article, the modelling of changing conditions and future investment opportunities is strongly connected to flexibility which, in turn, is valuable for avoiding lock-in situations.

2 Literature review

This chapter presents earlier work related to the work of this thesis. The first section (Section 2.1) presents literature on strategic decision-making and planning with specific applications to biorefinery opportunities in the pulp and paper industry although without any explicit consideration to uncertainties. Uncertainty is instead in focus in Sections 2.2−2.4, but there with a wider scope of applications. The literature reviewed in those sections is, however, related to the scope of this thesis in its applications to either biorefinery process design (Section 2.2), or investment optimization in other energy-related applications (Section 2.3). Section 2.4 specifically discusses the modelling of technology development.

The vast number of other applications in process design, management, planning and scheduling in which various types of uncertainty have been considered are beyond the scope of this literature review. The interested reader is instead referred to extensive reviews that have been published by, for example, Sahinidis [2] and Verderame et al. [3], which span multiple sectors, various forms of uncertainty and different modelling frameworks (see also [4] in which a comprehensive literature review is presented as well as an illustrative example of issues on problem formulation and solution). Literature on process integration and biorefinery technologies for the pulp and paper industry is reviewed in Chapter 4.

2.1 Strategic decision-making in the pulp and paper industry

Long-term strategies in the pulp and paper industry should consider the future opportunities the industry is facing, for example, with regard to new biorefinery concepts. The strategic decisions can be analyzed and optimized on different system levels and from various perspectives.

In a series of papers, Chambost et al. [5–8] have systematically analyzed the opportunities connected to biorefinery implementation in the pulp and paper industry from a strategic business perspective. The studied aspects of the biorefinery business models include the enterprise transformation required and the competitive assessment of product portfolio designs [6], partnership selection and long-term vision [7] and supply chain analysis [8]. The same research group has also proposed an integration of product portfolio design and supply chain design for the forest biorefinery [9].

Kangas et al. [10] have developed a model to study how investments in biofuel production in pulp and paper mills depend on price and policy structures. The model has a policy perspective on the whole Finnish pulp and paper sector, but allows for plant-level profit maximization of a number of mills. In the model, the total biofuel demand is fixed, representing a political target. The purpose is to see how the investment behaviour of the Finnish pulp and paper industry is affected by different subsidies to reach this target. This model formulation enables the prices of, for example, pulp, wood and heat to be determined within the model (endogenous), and therefore cannot be considered uncertain. The results of the study show that the choice of policy instrument affects direct policy costs, the input choice in the biofuel production, the prices of pulpwood and forest residues and the number of established biorefineries. However, the study has a rather short-term perspective, it does not include the impact of climate policies and it does not consider other alternatives than biofuel production for increased wood use in the forest industry.

The potential for different technology pathways for pulp mills in Europe has been investigated by Jönsson [11]. The pathways include both traditional energy technologies such as heat and electricity production and emerging biorefinery processes such as lignin extraction and black liquor gasification. While the overall aim of this work was to investigate the potential for industry-wide implementation of different technologies, processes and system solutions, it also includes detailed analyzes of mill-specific investment opportunities. However, although a number of parameters are varied in a scenario analysis, uncertainties and long-term change were not considered explicitly.

2.2 Uncertainty in biorefinery process modelling

During recent years, a number of studies have been published on the optimal synthesis and evaluation of biorefinery process designs. However, studies that do not explicitly consider uncertainties are not covered in this literature review. Instead, the reader is referred to a book chapter on the design of integrated biorefineries by El-Halwagi [12] and a paper by Kokossis and Yang on system technologies for biorefinery synthesis [13] that review much of the work in this field. References to studies evaluating biorefinery concepts for the Kraft pulp and paper industry are provided in Chapter 4. For the vast number of articles on general process design under uncertainty which are not specifically aimed at biorefinery applications, the reader is referred to the afore-mentioned review articles [2, 3].

Methods for risk analysis in early stage biorefinery process design have been reviewed by Hytönen and Stuart [14]. They particularly discuss the uncertainties that are essential to forest biorefinery decisions. These include process-inherent uncertainties for emerging biorefinery technologies, feedstock and product market prices, the scaling of laboratory/pilot scale models to full scale operation, policy instruments and the availability of financing. Especially the external uncertainties are claimed to be of interest at the early design stages (see also [15] for a classification of different sources of uncertainty in process design). Hytönen and Stuart [14] conclude that a systematic accounting of uncertainties is uncommon and the results are usually not used explicitly in the decision-making. Instead key parameters are typically varied for a fixed design to improve the understanding of the impact of the parameters on the economic performance.

This kind of post-optimization sensitivity analysis has been a common method for considering uncertainty in the optimization of investments in process integration and/or forest biorefineries (see e.g. [9, 16–20]). In some of these studies, the co-dependency of parameters is captured by using a scenario-based approach instead of individually varying the uncertain parameters. A development of consistent energy market scenarios for the evaluation of process integration investments under different future conditions was initiated in our research group by Ådahl and Harvey [18] and later continued by Axelsson and Harvey [21, 22]. These scenarios have been used in numerous recent studies to analyze the effect of different realizations of the uncertain energy market parameters, for example, for pulp and paper industry applications [23–33]. The original scenarios suggested by Ådahl and Harvey [18] modelled a path of changing conditions over time. However, the only investment opportunity considered was at the start of the studied time period. Consequently, the flexibility of making new investments as reactions to changing conditions was not considered. The modelling of scenarios as pathways of change was abandoned when the modelling of consistent scenarios was systematized through the development of a calculation tool [21]. In later updates of the tool and scenarios, multiple, but independent time points were again included.

One approach for dealing with uncertainties in the process design of forest biorefineries has been proposed by Hytönen and Stuart [34]. They have compared different process design alternatives for the production of biofuels in an integrated forest biorefinery. A large but limited set of pre-defined, distinct process designs were evaluated (and consequently, no optimization was involved). The suggested approach is based on Monte Carlo simulations and uncertainty is considered for energy and product prices. A sensitivity analysis was performed to identify the variables with the largest impact on the profitability of the process designs. These variables were then selected for the Monte Carlo risk analysis with the purpose of screening out non-promising design options. The methodology may therefore be suitable as a screening step, before using the methodology proposed in this thesis to optimize mill-specific process integration decisions. Another methodology for early-stage design screening based on multicriteria decision making has been suggested by Cohen et al. [35].

Another framework for decision analysis regarding the design of biorefineries has been suggested by Sharma et al. [36]. The problem assessed is similar to the one considered in this thesis, but involves the greenfield design of a biorefinery as opposed to the efficient implementation of biorefinery processes at an existing pulp mill enabled by ambitious heat integration. Furthermore, although the framework suggested in [36] includes a real options module to account for uncertainties in product demands, prices and biomass yields, this real options module was not yet implemented in [36]. The model presented in [36] thus assumes constant fuel and electricity prices. Process integration through the use of waste streams as raw materials and through centralized utility generation is considered in [36]. Unlike our work, however, heat integration within and between the biorefinery processes and the pulping process is not included.

Heat integration for optimal utilization of biomass and energy has, however, been included in the framework for biorefinery optimization proposed by Sammons et al. [37]. The optimization methodology proposed in [37] includes a library of processing routes and their corresponding economic and environmental performance metrics that have been identified using a strategy based on simulations, experiments and process integration tools. The goal is to determine the optimal product portfolio and process configuration of a biorefinery that may be constructed as a greenfield project or retrofitted onto an existing facility. However, also in the work presented in [37], optimization under uncertainty has been mentioned, but left for future work.

Tay et al. [38] have proposed an approach for considering uncertainty when determining the optimal retrofit of an existing pulp and paper mill to an integrated biorefinery. While the system studied is similar to the one in this thesis, the application differs in several respects. While the work presented in [38] considers uncertainty in biomass supply and products demands, this thesis considers uncertainty in the prices of energy and biorefinery products and in the investment costs of new technology. Furthermore, in the approach proposed in [38], the heat integration of the integrated biorefinery is not explicitly included in the optimization model. The approach suggested in [38] is based on robust optimization. Unlike stochastic programming, which is used in this thesis, the robust optimization approach does not take advantage of assumptions about probability distributions and it does not model any recourse decisions as reactions to unfavourable outcomes.

Liu et al. [39] have proposed an approach to consider uncertainty in the design of a polygeneration energy system which – with biomass feedstock – would typically be a biorefinery. The methodology is, like the one proposed in this thesis, based on stochastic programming. Uncertainty is considered in energy prices and demands, which are assumed to follow normal distributions, but no long-term trends are considered. Unlike the methodology proposed in this thesis only one design stage in which investment decisions can be made is modelled.

Uncertainty has gained increased attention in recent years also in the optimization of the supply chain networks of the biorefineries (see e.g. [40, 41]). In the supply chain optimization, the objective is to optimize the number, location and size of the biorefinery processing plants as well as the transportation of material in the network. The methods used in the cited studies are based on stochastic programming with a wide range of parameters considered to be uncertain, including the prices of raw material and products. However, while the investment problem considered in this thesis concerns the retrofit of one single, existing pulp mill, several greenfield biorefinery plants are subject to optimization in the supply chain models.

The potential for future technology pathways in the pulp and paper industry has been studied by Chladná et al. [42] who investigated the expected optimal timing for CO_2 capture investment under uncertainty. In their study, biomass, electricity and carbon prices are modelled as uncertain, correlated parameters. Both a recovery boiler and a black liquor gasifier are considered for the mill's steam production, but as two separate cases. However, the steam demand of the pulping process is assumed to be fixed. Consequently, no process integration opportunities are considered and only three distinct process configurations are modelled. The model thus allows for the optimization of the investment in CO_2 capture, but does not consider any competing technologies. The model developed by Chladná et al. [42] is based on a real options approach. The real options approach is commonly used for investment optimization under uncertainty, including several applications related to energy (see Section 2.3).

2.3 Investment under uncertainty – Other energy-related applications

A number of modelling tools can be used to analyze the investment decision problem under uncertainty. The reader is again referred to the review articles on optimization under uncertainty [2, 3]. Two interesting recent examples are the inexact fuzzy-stochastic modelling approach [43] and the interval fixed-mix stochastic programming method [44] both of which account for uncertainties that cannot be described by probability distributions only. In the models presented in [43, 44], uncertainties can be expressed by fuzzy sets and interval values as well as by probability distributions. The approach could therefore be of interest for the uncertainties considered in this thesis, for which probabilities are sometimes difficult to establish (see further Section 6.3.4). Stochastic programming, which is applied in this thesis, has been incorporated in many energy system models to account for uncertain energy-environment policies. Examples are the stochastic versions of the MARKAL model [45, 46] and the stochastic MESSAGE model [47]. All of the studies [43–47] are, however, used for analyzes on regional and/or global scale of energy-related sectors. A complete review of studies on the system level will not be provided here. Instead, emphasis will be on studies with the scale of an individual plant or firm as assumed in the work of this thesis.

The stochastic programming model of an absorption cooling system presented by Gebreslassie et al. [48] is an example of the optimization of a single energy conversion process. In their work, energy costs are considered uncertain and the problem is formulated in a two-objective, stochastic programming model for the minimization of expected total costs and associated risk. Dubuis and Maréchal [49] have proposed a stochastic optimization approach based on evolutionary algorithms for the design of an energy conversion process. However, the results published do not state which parameters are considered uncertain and how their probability functions have been defined. Furthermore, this approach seems to be intended for one single energy conversion process rather than the whole energy system of all integrated processes in an industrial plant. An approach based on evolutionary algorithms has also been proposed by Pettersson and Söderman [50] for the design of heat recovery systems in paper machines. They consider uncertainty in process parameters which are assumed to follow normal probability distributions. Also in their work, the system studied is limited to one single process part (the paper machine) rather than the whole pulp and paper mill.

Within the economic field, variations and uncertainty are often dealt with in a real options framework (see e.g. [51]). Several studies apply the real options approach to investments in power generation in the energy sector (see e.g. [52–56]). These studies, typically, investigate how climate policy uncertainty – sometimes in combination with energy market uncertainty – affects the investment behaviour of private companies. They all confirm the importance of accounting for uncertainty and timing.

A few real options studies have been applied to the industrial sector and investments in, for example, heat production and energy efficiency. Wickart and Madlener [57] have developed a model for the choice between combined heat and power production and heat-only production for an industrial firm. The model accounts for uncertainties in energy prices and determines the best technology choice as well as the timing of the investment.

A study of investments in energy saving technology for the greenhouses in the horticultural sector [58] is another example of a study investigating energy consumer side investments using a real options methodology.

As mentioned in Section 2.2, the real options approach has also been applied to the pulp and paper industry by Chladná et al. [42]. While their study has considered a few, discrete process configurations, the real options approach is, usually, not suitable when a more detailed process modelling is required. This is the case, for example, when considering investments in process integration and several competing technologies for which the capacities are not predefined. This implies an optimization, not only of discrete investment options, but also of continuous process variables, such as equipment sizes and heat flows that are, in addition, related through, for example, heat balances and capacity constraints (see also Section 5.1 for a discussion about the method selected in this thesis).

2.4 Uncertainty in investment costs

In energy system models, the investment cost development of emerging technologies is commonly modelled by so-called learning curves (see e.g. [59]). However, since the learning curve approach assumes that the rate of technological change depends on variables that are determined within the model, it is not applicable to studies that assume the system boundaries around a single plant.

There are a few studies that have been applied to such plant-perspective, energy-related investments in which the technology cost is assumed to be uncertain. Fuss and Szolgayová [60], for example, have built on their real options framework for investments in the electricity sector (see [54, 55, 61]) in their approach to modelling uncertain and exogenous technological change. They include uncertainty in the arrival rate of innovations that reduce the cost of emerging technology, but consider the cumulative technical change to be fixed. Thereby, it is possible to analyze uncertainty about the technical change process – comparing frequent innovations that lead to marginal cost improvements with rare occasions of drastic cost reductions. On the other hand, the rate of technical change is modelled as a deterministic parameter, for which two scenarios are analyzed – a high and a low rate of change.

Building on the same framework again, Zhou et al. [62] have modelled the real options problem of investment in CO_2 capture and storage (CCS) in China's power sector. They also model the rate of technological change as a deterministic parameter and use two different scenarios for the cost development of the CCS technology – one with technical change and one without. In both of these studies, the expected investment cost is assumed to decrease with time according to an exponential curve. However, as previously mentioned, learning is typically independent of time, and such a function would only be valid if experience of the technology increases at a constant rate over time.

3 Objectives and scope

As shown in Chapter 2, there are very few studies of process integration decisions under uncertainty. The few studies published either consider other decision variables and/or uncertain parameters than those studied in this thesis, or model the decision problem in a way that does not adequately capture that the decisions are made before knowing the future outcome of the uncertain parameters (see also Chapter 5, Section 5.1 where the method chosen in this thesis is motivated).

There are, however (see Chapter 2), a number of studies that consider investment decisions under uncertainty for other investments than process integration. The methods used in those studies cannot, however, be directly applied to the decision problem considered in this thesis. For process integration decisions, there are not only a limited set of discrete investment options, each being associated with a certain cash flow. Instead, there are constraints on how investment options can be combined. The resulting cash flows cannot be allocated to specific investment options; they depend on both the combination of technologies and energy-saving measures implemented and on the operating decisions, the optimal values of which depend on the values of the uncertain parameters (see further Chapter 4).

Consequently, there is a need for a methodology that optimizes investments in process integration under uncertainty. This leads us to the objectives of this thesis which are presented in Section 3.1. Section 3.2 then defines the scope and delimitations of the work.

3.1 Objectives

As mentioned in the introduction, the overall aim of this thesis is to propose a methodology for the optimization of strategic process integration investments under uncertainty, and to illustrate how this methodology can be used to achieve a better understanding of investment decisions for process integration and biorefinery implementation in pulp mills. Based on this aim, the objectives of the work can be divided into two categories: methodology development and the application of the methodology. The objectives are elaborated in more detail below.

Methodology development

The objectives connected to methodology development include:

- Formulation of an optimization model that considers
    - an economic objective to maximize the value of investments,
    - investments for process integration and biorefinery implementation in pulp mills,
    - current and future investment opportunities, modelled in multiple time steps,
    - uncertainty in energy market parameters such as energy prices and policy instruments, and
    - technological uncertainty with regard to the investment cost of emerging technologies.

- Development of a methodology for the application of the optimization model that describes
    - the required data and constraints for the process integration measures and the energy and biorefinery technologies,
    - the required data for and modelling of scenarios representing the uncertain parameters, and
    - the results obtained and suggestions for evaluation of further results.

Application of the methodology

Another objective of the project is to illustrate the application of the methodology through a number of case studies. The overall objective connected to this use of the methodology is to achieve an improved understanding of the robustness and flexibility of strategic investment decisions. This objective can be reached by illustrating which factors can influence investment decisions in a long-term strategic perspective. For example, the importance of making the right series of decisions in order to avoid lock-in effects has been studied.

3.2 Scope

When this project started, the methodology was aimed at energy-intensive industries in general and focus was on process integration investments for energy savings. The first case study, representing a pulp mill, made evident that even if the basic methodology is the same, generality is quickly lost when the model and data are adapted to mill-specific conditions. The following case studies were therefore chosen to resemble the first one in order to focus the efforts on methodology development. The Kraft pulping industry also had the advantage that input data was available from a number of previous research projects that have investigated process integration opportunities with detailed technical and economic evaluations.

The work of this thesis has a clear interdisciplinary character; it is based on process integration, mathematical optimization and investment evaluation and has more or less strong connections to, for example, operations research, decision theory and business planning. As such, the work is based on knowledge from both technical and non-technical scientific fields. This is also the reason why direct cooperation with researchers from the department of mathematical sciences was initiated. There has, however, been a gradual shift in the emphasis of the work: from the mathematical modelling and methodology development to the results from its application. The first papers thus focus on how to identify optimal investments, while the later papers to a greater extent investigate and explain why some investments are better than others.

In its strategic planning, a pulp and paper firm needs to consider a number of changes in society, such as: policy and market changes due to increased environmental concerns, demand variations for different products, and a changing competition situation [63]. Biomass availability and quality will impact the product and process selection [64]. Existing and possible future forms of cooperation and agreements with suppliers, customers, and other business partners are also important to consider [7]. Furthermore, the firm should consider the marketing situation and competition with other firms and define their specific weaknesses and strengths regarding, for example, their products, their supply chains and the technical infrastructure of their mills [5]. Systematic methodologies for the identification of promising products and process designs considering these business aspects of biorefinery strategies are important, and can be used in connection with the methodology proposed in this thesis. Such methods could, typically, be used to identify a number of promising biorefinery options to include in our model, and to screen out non-promising options.

The methodology proposed in this thesis is a new tool for strategic decisions with a focus on process integration opportunities in existing plants. As such, it will contribute to a deeper understanding of the long-term consequences of different decisions from a process technology and systems perspective with emphasis on energy-efficient implementation. Together with other methods for strategic decision-making it will constitute one part of the comprehensive efforts required to improve the decision making regarding biorefinery implementation in the pulp and paper industry.

A pulp mill is usually only one of many mills owned by a firm, and therefore subject to overall firm strategy. Overall firm strategy might include closing down inefficient mills and increasing the production at other mills. The strategy might also include plans for biorefinery implementation in which certain emerging technologies are considered more promising for the firm than others. The overall firm strategy is, in the work of this thesis, considered to be a fixed pre-condition for the investment planning at a specific mill. The mill is assumed to be kept in business, and the production is either assumed to be constant over the whole planning period, or assumed to be changed according to an already set plan with regard to both time and magnitude. The firm strategy is further assumed to delimit which biorefinery options are important to include in the investment plan optimization.

Furthermore, for the pulp mill biorefinery processes considered in this thesis, mainly the pulp wood residues (e.g. bark and black liquor) are used as feedstock. The cost for pulp wood is not considered in the models, since the pulp wood input is determined by the assumed pulp production. Additional biomass might be needed for biorefinery processes requiring large amounts of biomass. In the case studies included in this thesis, this additional biomass is assumed to be bark or other wood residues. The dependence of the biomass cost on the relation between biomass availability and demand is not explicitly modelled. It is, however, possible to, for example, differ between a boiler type with a large capacity and a boiler type with a small capacity and set a higher cost of biomass used for the large-capacity type.

Figure 1 illustrates the scope of this thesis in relation to firm strategy and uncertain prices and costs.

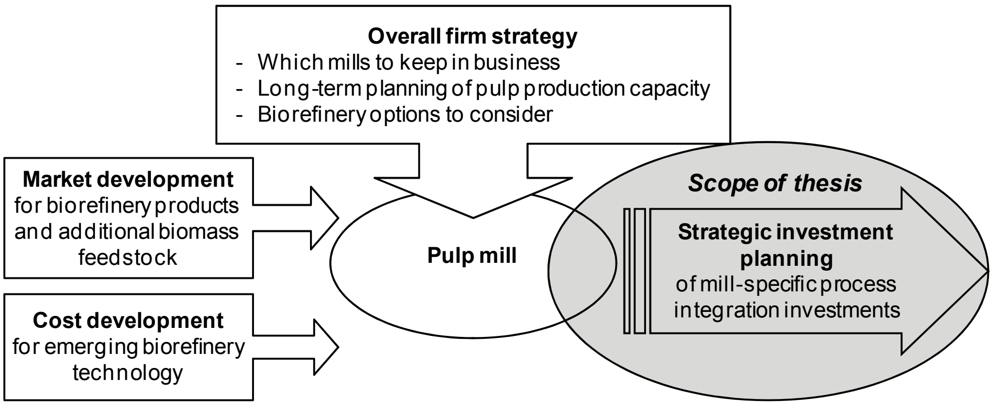

FIGURE 1: Illustration of the simplified system delimitation assumed in this thesis. Changes in energy market conditions and technology development, but also in the overall firm strategy are considered exogenous, i.e. beyond the control of the pulp mill. As a response to these changes, the pulp mill needs to identify an investment plan for process integration and biorefinery implementation.

Although the scope is limited to mill-specific investments for a given firm strategy, the methodology proposed in this thesis cannot be a ready-to-use tool since work is always needed to adapt data and modelling to mill-specific conditions. Especially the process integration studies required to obtain data for the energy efficiency measures are often time-consuming. Also the models for the uncertain energy prices, and other economic data usually need to be adjusted; comprehensive understanding of the methodology and models is therefore required. It is therefore important to emphasize that the methodology is intended for strategic projects in which substantial work efforts are allowed for the achievement of a deeper comprehension of the modelling requirements and the input data needed. The costs of such work efforts can, however, normally be easily motivated in comparison to the many times higher costs of the strategic investments evaluated.

4 Process integration for efficient pulp mill biorefineries

This chapter briefly describes the pulp mill biorefinery (Section 4.1), the concept of process integration (Section 4.2) and possibilities for energy savings and new technologies in Kraft pulp mills (Sections 4.3 and 4.4). Section 4.5 discusses the important relations between process integration, energy savings and the implementation of new technologies and biorefinery processes into existing mills.

4.1 The pulp mill biorefinery

There are several definitions of the term biorefinery. All definitions, however, involve a description of a plant in which biomass is upgraded to one or more valuable products. Depending on the context, different biomass feedstock, technologies and products are considered for the biorefinery. For a more elaborate description of what a biorefinery is, including a number of definitions, the reader is referred to a book chapter by Berntsson et al. [65].

One potential feedstock to biorefineries is woody biomass. The pulp and paper industry, which already uses a wood biomass feedstock, has therefore clear opportunities connected to biorefinery implementation. Many mills already produce, for example, electricity or district heating in addition to pulp and paper. This is one way of improving the overall energy efficiency of the mill and thereby also profitability. Other possible products are wood pellets, dried bark, and different kinds of biofuels, chemicals and materials. There are also opportunities for the integration of CO_2 capture plants. The adoption of different biorefinery concepts into the pulp and paper industry is also motivated by the need for a diversified product portfolio following the negative price trends of pulp and paper. According to a recent study [66], wood-based biofuel and chemical production is considered an important business opportunity in the forest industry. The pulp and paper industry with its existing biomass infrastructure also has a competitive advantage over other potential biorefinery actors.

In this thesis, investment strategies for this kind of pulp mill biorefineries – also called forest biorefineries or integrated forest biorefineries – are investigated. An important assumption in this thesis is that the mill will continue to produce pulp in addition to energy and other products. Overviews of the opportunities for the integration of biorefinery processes into the Kraft pulp and paper industry are given, for example, in [6, 12, 67, 68]. For studies investigating the technical and economic potential for specific technology pathways, refer to Section 4.4.

4.2 Process integration for improved energy efficiency

Process integration refers to a system-oriented view on process design where the interaction between process units is considered and the aim is to optimize the efficiency of the whole system rather than sub-optimize separate parts of the process.

Pinch analysis is one method for process integration that can be used to identify measures for improving heat integration both within the pulping process and between the pulping process and the biorefinery process. The basics of pinch analysis are presented in "User Guide on Process Integration" by Linnhoff [69]. Revised versions of the user guide are also available [70, 71]. In addition, the reader is referred to books by Smith [72] and Klemeš [73].

Pinch analysis can be used for retrofitting of existing processes. The method consists of the following steps:

1. Collecting stream data (heat loads and temperature levels) for all streams that require heating and cooling in the process and for hot and cold utilities.
2. Targeting of theoretical minimum hot and cold utility demands.
3. Mapping of the existing heat exchanger network design
4. Retrofit for improvement of the existing heat exchanger network to get closer to the targets identified in Step 2.

The data collection in Step 1 usually takes up the majority of the time spent on the analysis.

The results from a pinch analysis – that is, the identified opportunities for improved heat integration – serve as input to the methodology and models presented in this thesis. However, no pinch analysis has been performed within the scope of this work. Instead the results from other research projects [27, 74–79] have been used as input.

4.3 Energy savings in Kraft pulp mills

All the pulp mills studied in this thesis are (models of) market Kraft pulp mills. Through heat savings, such mills can achieve a surplus of heat, which, for example, can be used to supply heat to a new biorefinery process. Increasing the heat surplus improves the potential for efficient integration of new processes.

In the process industry in general, heat savings can be achieved through a number of different measures that can be divided into the following categories:

- Improved internal heat exchange
- More energy-efficient equipment
- Use of excess heat for more efficiently integrated units, for example, thermally integrated separation processes such as distillation and evaporation plants.
- Heat pumps for improved heat recovery.

For the pulp and paper industry, Martin et al. [80] have identified and discussed various opportunities for improving energy efficiency. Much research has also been aimed specifically at process integration in existing Kraft pulp mills (see e.g. [81–90]).

4.4 Technologies for Kraft pulp mill biorefineries

The potential for the efficient integration of various technology pathways with the Kraft pulping process has been studied extensively by our research group as well as by others. Below, examples of promising technologies for future pulp mill biorefineries are presented. References are provided to previous research in which these technologies have been studied from a process integration perspective.

Included in the case studies of this thesis

- Increased electricity generation (see e.g. [76, 91])
- Reduced bark use (see e.g. [33])
- Lignin extraction [75, 76]
- Export of heat for district heating [27, 92–94]
- CO_2 capture [42, 95–97]

Not included in this thesis

- Hemicellulose extraction [87, 98–100]
- Black liquor gasification with motor-fuel production [24, 101–105]
- Gasification of biomass [29, 106]
- Upgrading of biomass through, for example, drying and pelletizing [32]
- Converting the pulping process to ethanol production [107]

An implication of integrating many of these processes (e.g. reduced bark use, hemicellulose and/or lignin extraction, and upgrading of biomass) is that they lead to a reduction in the steam production at the mill since biomass is used for other purposes than for internal fuel. This can be compensated by imports of external fuel, but for efficient and economic implementation, the reduction in steam production should be compensated by energy savings to reduce the demand for process steam. This, in turn, leads to a reduction in the electricity production in the back-pressure turbines at the mill. Therefore, most of the biorefinery technologies involve a trade-off, both directly and indirectly, with electricity production.

4.5 Process integration in pulp mill biorefineries

Biorefineries can be implemented as stand-alone plants. However, if the biorefinery processes are integrated with an existing process industry plant such as a pulp mill, the overall efficiency of the combined plant can be much higher than that of corresponding stand-alone plants (see e.g. [104, 108, 109]). The pulp mill could either have a surplus of steam/heat, which can be used to cover the heating demand of a biorefinery process, or, alternatively, it could have a demand for heat, which can be supplied by excess heat from a biorefinery process. Either way, the total demand for heating and cooling is reduced, and the efficiency and profitability of the combined process is improved. There are usually also opportunities for the integration of chemical and/or material streams between the processes.

Different types of pulp and/or paper mills vary in their potential for the efficient heat integration of a biorefinery process. The potential depends on the energy balances of the mill and the temperature levels of its heating and cooling demands. The case studies of model mills included in this thesis all represent market Kraft pulp mills that can achieve a surplus of energy from their wood raw material. They therefore have the potential to supply heat to new biorefinery processes or to implement technologies such as lignin extraction that lead to a reduced steam production.

Heat integration within a biorefinery process leads to a reduction of its heating and cooling demand in the same way as heat integration within the pulping process leads to energy savings. However, heat integration within a process will also affect its temperature characteristics. Consequently, the potential for integration between the biorefinery process and the pulping process may also change. Therefore, heat integration should be considered on different system levels both within and between processes.

While several of the technology pathways listed in Section 4.4 can be combined, the effects of implementing a combination of different technologies and processes into the pulp mill are typically not additive. Both the investment cost and the opportunities for heat integration may vary depending on which other technologies and processes are implemented and how they are designed, especially with regard to their temperature-heat profiles. It is therefore important that the chosen optimization approach enables the correct modelling of the relation between different process integration decisions.

5 Methods

This chapter describes the methods for mathematical optimization and economic evaluation on which the developed methodology is based. Arguments for the choice of method and evaluation criteria are also presented. The chapter also includes the general economic assumptions used in the investment evaluation.

5.1 Optimization of investments under uncertainty

The methodology developed in this project is based on stochastic programming. Before the method of stochastic programming is described in Section 5.1.1, some alternative methods for considering uncertainty in investment optimization are also discussed.

The effect of parameter uncertainty on an optimal solution and its value can be tested using sensitivity analysis. The sensitivity to variations can be analyzed by varying one parameter at a time or by using scenario analysis in which the co-dependency of parameters is captured by a packaged sensitivity analysis. A sensitivity analysis is a way of evaluating the robustness of a given solution and identifying the parameters that have the greatest influence on the solution and its value. Advanced methods for the analysis of uncertainty in deterministic models also include Monte Carlo methods and multi-parametric programming. Monte Carlo analysis is based on sampling from the probability distributions of the uncertain parameters and can be used to evaluate the probability distribution of the value of a solution (see e.g. [110])[2]. Multi-parametric programming (see [111] for a forest biorefinery scheduling application) aims at defining a function that maps each point in the range of possible parameter values to a specific optimal solution (see e.g. [112]).

The methods mentioned above enable the identification of a number of solutions that are each optimal for a given set of parameter values. They do not, however, provide a way of determining which solution is the best one overall. The solution that is optimal under uncertainty might not be optimal for any single realization of the uncertain parameters. Under uncertainty, solutions that provide a way to hedge against uncertainty and to react to unwanted outcomes are usually the best ones. The value of this robustness and flexibility is captured only if the uncertainty is explicitly incorporated into the

[2] Monte Carlo can refer to a variety of methods that are all based on estimations of mean and variance by sampling. Here, we refer to methods for risk analysis.

optimization model and decisions are modelled to be made before the realization of the uncertain parameters (see Section 5.1.1).

The real options approach (see e.g. [51]) is another method used for investment decisions under uncertainty which properly models a decision structure – with decisions made with imperfect information about the future. The real options theory employs a view on investments, uncertainties and timing that corresponds to that of this thesis. However, the solution methods most commonly used – dynamic programming and contingent claims analysis – were judged inadequate in terms of the potential for process modelling that is required since the allocation of energy and cash flows to certain investment options is non-trivial (see Chapter 4). We have therefore chosen to base our methodology on a multistage stochastic programming approach. Since the objective of the optimization model is to maximize an expected value, and both the choice of investments and their timing is optimized, the problem solved is, actually, essentially a real options investment problem. As such, all option values of alternative investments, including the option value of waiting, are simultaneously considered. The method of stochastic programming is described in Section 5.1.1.

Other methods for optimization under uncertainty include fuzzy programming methods (see e.g. [113]). These methods can be used when no information is available on the probability distributions of the uncertain parameters. Instead the uncertain parameters are modelled as fuzzy numbers. Although the probability distributions of the uncertain parameters considered in this thesis are difficult to establish (see Section 6.3.4), assumptions can usually be made regarding the probability of different outcomes. This information cannot be utilized in a fuzzy programming model, but is used in the stochastic programming approach.

5.1.1 Stochastic programming

Stochastic programming is typically used when a decision is made before knowing which values of some uncertain parameters will be realized and thus with imperfect information about the future. As a result, hedging against unfavourable outcomes of uncertain parameters leads to solutions with the best average performance.

In stochastic programming, the goal is to find a set of decisions that is feasible[3] for all possible outcomes of uncertain data and that maximizes the expected value of some function of the decisions and the uncertain parameters. To calculate the expected value, the probability distribution for the uncertain parameters must be known or estimated. A stage is a point in time when decisions are made. Between stages, new information becomes available. When the outcome of the uncertain event is revealed, new decisions – recourse decisions – can be made to adapt to unfavourable situations. This structure,

[3] A solution is feasible if it fulfils all the constraints imposed by the optimization model. Throughout this thesis, uncertain parameters are included in the objective function only and not in the constraints. Feasibility is therefore not affected by uncertainty in this case.

'decision – realization – recourse', represents a two-stage recourse problem[4]. Stochastic programming problems are not limited to two stages. The stochastic programming model used throughout this thesis is a multistage recourse model.

The field of stochastic programming evolved during the 1950s, initialized by George B. Dantzig [115]. A number of books have since been published, covering the theory of stochastic programming (see e.g. [116, 117–119]). The reader is also referred to a tutorial by Sen and Higle [120], and a review article by Birge [121]. The model used in this thesis is a mixed-integer linear programming (MILP) model (see also Section 6.2.4). Stochastic integer programming is described, for example, in [119, 122–126].

In its basic form, the stochastic programming approach assumes that the decision-maker is risk-neutral. Risk aversion can be modelled by including some risk or variability measure in the objective function (see e.g. [120]) or as a separate objective function transforming the model into a multiobjective optimization model. The inclusion of risk is left for future work (see Section 10.1).

Scenario-based modelling

In this thesis, the probability distribution is modelled as a discrete distribution with a finite number of possible outcomes of the uncertain parameters. This leads to a scenario-based modelling approach. Figure 2 shows an example of a scenario tree with four stages. Every node n in the scenario tree corresponds to a specific realization of uncertain parameters at a specific stage.

Node $n = 0$ is called the root and corresponds to the stage for which all parameter values are known at the beginning of the process. Each new level of nodes in the scenario tree (e.g., the nodes $n = 3,\ldots,7$ in Figure 2) constitutes a new stage in the decision process. A scenario refers to the realization of a root-to-leaf path in the tree (e.g., the nodes $n = 0, 2, 6, 13$ in Figure 2). By construction, any node n except the root node has exactly one parent node $p(n)$ at the previous level. Each node n can, however, have any finite number of child nodes at the next level. The level of a node n is denoted by $\ell(n)$.

If the probability for each of the scenarios, or paths, is known or assumed, the probability for each of the nodes of the tree can also be determined as the sum of the probabilities for all scenarios passing through that node.

[4] As an alternative to the recourse-based formulation, stochastic programming also includes the probabilistic, chance-constrained programming approach (see e.g. [114]). This approach focuses on the probability of meeting feasibility and is therefore not relevant in this thesis, since feasibility is not affected by uncertainty here.

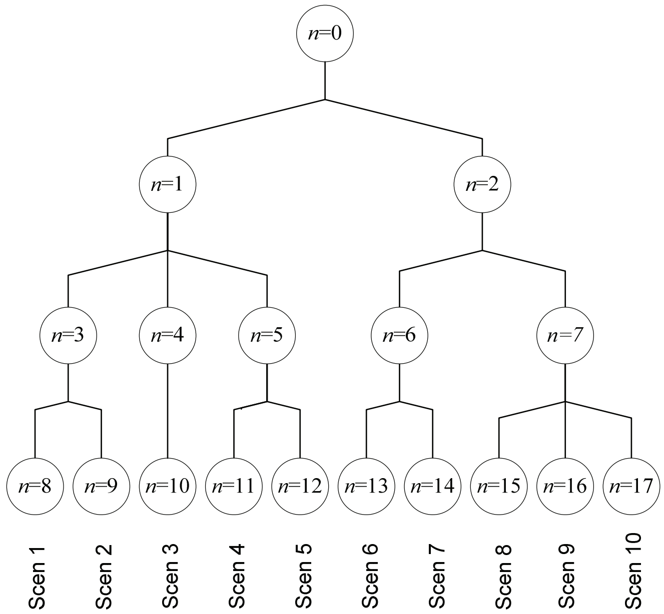

FIGURE 2. An example of a four-stage scenario tree.

5.2 Investment evaluation

The economic objective function of the optimization model is the net present value (NPV). This economic optimization criterion is recommended in textbooks on economic analysis (see e.g. [127]) and has been shown to be suitable for strategic process design and energy efficiency investments [128, 129]. Pintarič and Kravanja [128] have analyzed the characteristics of the optimal process flowsheet designs obtained with various economic objectives, and have concluded that the NPV is most appropriate, since it represents a thorough trade-off between quantitative criteria (large cash flows) and qualitative criteria (profitability/rate of return).

Various other profitability measures can be applied for the optimization of investment decisions. Common criteria include minimization of total costs (investment cost and operating costs) or maximization of profit (difference between incomes and costs) (see [128] for a brief survey of economic objective functions used for process flow sheet design). Minimization of the payback time (total costs divided by annual cash flows) is another common economic measure.

However, for strategic investments, like the ones considered in this thesis, it is important to consider the time value of money. This requires an evaluation criterion that, unlike the ones mentioned above, accounts for the discounting of cash flows. For the total annual costs, or the annual net profits (ANP), this is achieved by annualizing the investment cost with an annuity that is calculated based on the assumed discount rate. Another economic measure that incorporates the time value of money is the internal rate of return (IRR) which is equivalent to the NPV unless some of the cash flows are negative (see e.g. [129]). The NPV is, however, more straightforward to include in the mixed-integer, linear programming model formulation.

Furthermore, economic criteria like the ANP require that investments are made at one point in time and that cash flows are constant over the project lifetime (see e.g. [127]). This is typically not the case for the investment plans optimized in this thesis. The NPV is therefore the best choice for the methodology proposed in this thesis. The NPV is described in Section 5.2.1 as follows.

5.2.1 The net present value

The economic measure used throughout this work is the net present value (NPV), which is expressed by the formula

$$\text{NPV} = -C_0 + \sum_{t=1}^{T} \frac{C_t}{(1+r)^t}, \tag{1}$$

where T is the economic lifetime (in years) of investments, r is the discount rate accounting for the time-value of money, C_0 is the initial investment, and C_t is the net cash flow (revenues minus costs) in year t. The higher the discount rate is, the less value future cash flows have. Consequently, a low discount rate and a long economic lifetime correspond to a strategic view on investments, while the opposite corresponds to a short-term view with a demand for short payback times (see Section 5.2.2 for the assumptions made with regard to these parameters in this thesis).

The traditional investment rule is to invest in a project if its NPV is positive. When more than one investment project is to be compared, the rule is to invest in the project that results in the highest positive NPV. Therefore, NPV is required not only to be positive but to be higher than the NPV of the other projects, that is, the so-called *option value* of making alternative investments. Here, in addition to immediate investments, the option value of waiting is also considered, which means that investments can be made later. Still, the investment rule is to follow the investment plan resulting in the highest expected NPV. The options of waiting or making alternative investments are called *real options* (see e.g. [51]).

5.2.2 General economic assumptions

The calculation of NPV requires assumptions for the values of the discount rate and the economic lifetime of the investments. The general assumptions made in the papers of this thesis are a discount rate of 9.3% over an economic lifetime of 30 years. In this section, the choice of a 9.3% discount rate over 30 years is argued for. Some other assumptions for the evaluation of the investment projects are discussed at the end of the section.

Paper I investigates the influence of variations in economic assumptions on optimal investments. As expected, the effect of uncertainty on investment decisions increases when the discount rate and economic lifetime are chosen to represent a more strategic view on investments (i.e., a low discount rate and a long economic lifetime). The methodology proposed in this thesis is therefore motivated primarily if economic assumptions represent such a strategic view (e.g. using the values mentioned above, 9.3% and 30 years).

Furthermore, for modelling reasons the economic lifetime is required to be at least as long as the analyzed time span of the investment plan (see also Appendix A, Paper III). In order to enable also future investments, for example, 15 years from now, to have a sufficiently long part of their economic lifetime within the analyzed time span, 30 years was determined to be suitable for the total investment plan. This choice results in an economic lifetime of 30 years, which is also motivated by the strategic view employed in the investment planning.

The discount rate is used to account for the time value of money. It typically includes a risk premium in addition to the interest rate. If uncertainty is explicitly incorporated into the investment decision model, as in a real options approach or in our stochastic programming model, the risk-free rate should be used (see e.g. [51])[5]. However, in our investment decision problem, investments in emerging technologies and new products are considered. It thus includes a number of risk factors that are not explicitly modelled, such as risks associated with short-term variations in the energy market, or risks associated with the performance and reliability of new technologies and system solutions. This would motivate a discount rate that is significantly higher than a risk-free rate of about 5%. An increase by 5%–20% has been mentioned for process investments in newer to riskier markets [128].

Finally, the combination of a 9.3% discount rate and a 30 year lifetime correspond to an annuity factor (also called the capital recovery factor) of 0.1. This value has been chosen to be suitable for strategic investments in research projects in cooperation with industry [131].

Other assumptions made in the model are listed as follows:

The time steps of the model are five years. The time steps correspond both to the interval between investment opportunities and to the scenario tree intervals. The choice of five years is partly because the scenario model is easily adapted to the scenario tool with which it is constructed (see Section 6.3). It is also a trade-off between model solvability and detail. However, it is also important that the intervals are long enough so that the development over one time step can be assumed to be a long-term change.

The residual value of investments is chosen to cancel out the annualized investment cost for the years remaining of the economic lifetime at the end of the analyzed time span. The modelling of the residual values is connected to the economic lifetime assumption. Arguments for the modelling of the residual value and a description of how it is calculated can be found in Appendix A of Paper III.

No limitations have been set for the total capital expenditure. Neither are there any limitations on how close in time to one investment the next investment can be made. These kinds of constraints are, however, very straightforward to add to the model if

[5] Tolis [130] has also suggested that the discount rate could be modelled as one of the uncertain parameters in a real options analysis. The proposed approach is, however, not readily applicable in our scenario-based stochastic programming model.

desired. Nevertheless, it is often better to run the optimization model as unconstrained as possible at first in order to avoid pre-optimization.

Simple assumptions have been used for the construction and project start-up. One year construction with 100% financing in the first year is assumed. Also, full capacity is assumed in the first production year the year after construction. The investment calculations can be more detailed in this respect, as well as with regard to some other economic assumptions. However, for most of the investments studied in this thesis, which mainly imply changes to an existing process rather than construction of a new process or plant, the assumptions used are appropriate. Nevertheless, if relevant, these assumptions are easy to change in the model.

No explicit consideration to environmental issues has been included. Implicitly, through the policy instruments included in the energy market scenarios, climate concern will affect the decisions. Constraints on, for example, CO_2 emissions, are easily added to the optimization model. We have proposed a multiobjective approach where the reduction of CO_2 emissions is added as a second objective [132]. However, this paper has not been included in this thesis. The difficulty of including emissions is mainly connected to data for the emissions associated with different energy carriers, especially since the timing of shifts in marginal production technologies are important in our model.

No direct accounting of risk has been included. Various methods exist for accounting of risk. One straightforward way to include a risk function in the model would be to add a constraint that, for example, sets a minimum value for the NPV in each scenario. Section 10.1 discusses possibilities for further work to include risk in the model.

6 Results – Developed models and methodologies

This chapter presents the core of this thesis work – the methodology for the optimization of process integration investments under uncertainty. The methodology starts with the identification and characterization of potential process integration and biorefinery investment options, and definitions of scenarios for uncertain future prices and costs. Using the optimization model developed, with adjustments for mill-specific conditions, the optimal investment plan with regard to maximization of the expected NPV can then be identified.

This chapter first presents the proposed methodology which considers uncertainty in energy market conditions only (Section 6.1). The accompanying optimization model is presented in Section 6.2. Section 6.3 describes the scenario models developed to represent the uncertain changes in the surrounding energy market. The main methodology was later extended with a proposed approach for including uncertainty in the investment cost development of emerging technologies. This approach and the scenarios proposed for the uncertain technology development are presented in Section 6.4. Finally, Section 6.5 describes an approach to use the methodology to study the effect of long lead times in the investment decision-making process.

A multiobjective formulation has also been suggested in which not only the economic objective, but also an environmental objective are considered. This work has been initiated in [132], but is not included in this thesis.

At the start of the methodology development, generality was aimed for in the sense that the methodology should be applicable to any type of energy-intensive industry. This was also how the methodology was presented in Paper I. In this chapter the methodology description has, to some extent, been adapted to the conditions typical for the pulp and paper sector since this has, gradually, received a greater focus in the research project (see Section 3.2).

6.1 Main methodology – for the optimization of process integration investments under energy market uncertainty

The methodology and the accompanying optimization model are naturally closely connected. Here they are, however, described separately. While the multistage stochastic optimization model is described in the next section, this section describes the methodology for using the optimization model to identify and analyze investments in process integration under uncertainty. The five-step methodology was proposed in Paper I and describes the steps needed to achieve the necessary input to the model (Steps 1–4), as well as some proposals for analyzing the results (Step 5). The main steps of the methodology are presented below, and their role connected to input and output of the optimization model is illustrated in Figure 3.

1. Identify the opportunities for energy efficiency investments.
2. Define the constraints on and effects of combining options.
3. Gather and compute input data.
4. Develop a scenario model.
5. Solve the model and analyze the results.

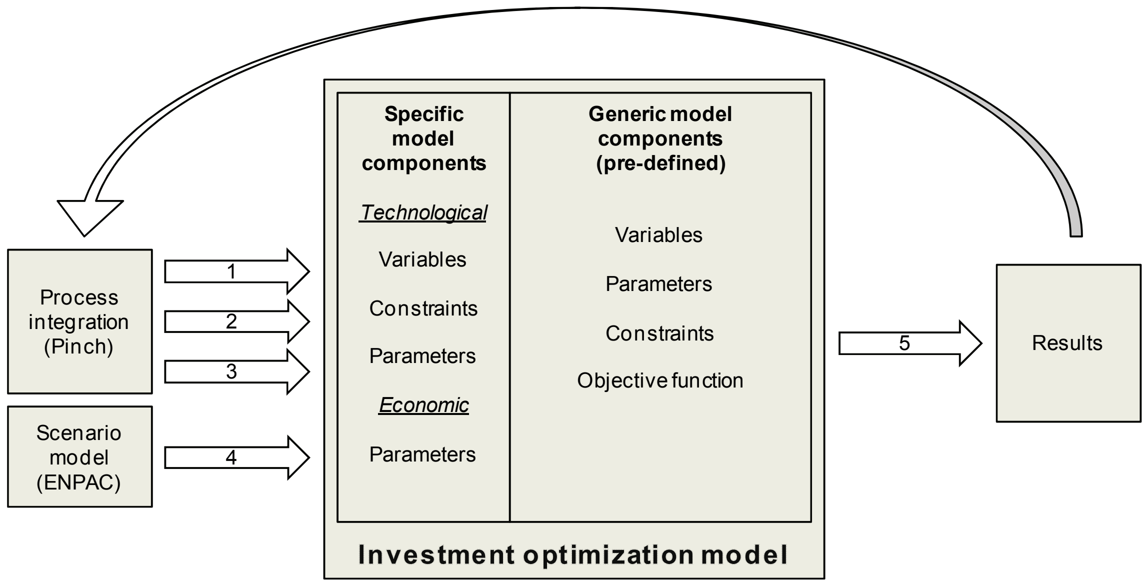

FIGURE 3. Overview of the optimization model and its relation to other tools and models through the five steps of the methodology.

Step 1 – Identify the opportunities for energy efficiency investments

The aim of the first step is to identify which investments opportunities should be included in the optimization model. This defines the set of investment variables in the model. In the model, investments are of two types, which can be labelled as heat-saving measures and energy-conversion technologies. The latter category can also include technologies or processes that will transform the pulp mill into a biorefinery, for example by the production of biofuels. It is assumed, however, that early-stage screening of promising biorefinery routes with respect to their business potential has been performed prior to the use of this methodology.

The heat-saving measures are defined in the model as fixed-cost investments that result in a fixed amount of heat (typically steam) saved. The potential for energy savings and opportunities for realizing this potential can be identified using pinch analysis (see Section 4.2). Examples of heat-saving measures include improved internal heat exchange for the reduction of heating and cooling utilities, more energy-efficient equipment such as efficient drying or separation processes, more efficiently integrated units such as using excess heat for distillation and evaporation and heat pumps for enhanced heat recovery.

For the energy-conversion technologies, on the other hand, the capacity is optimized in the model and the investment cost is given as a function of size. The output of an energy-conversion technology is a product such as electricity, dried bark, district heating, biofuel or some kind of biomaterial or -chemical for which the product output is a function of the steam flow allocated for that technology. These energy-conversion technologies offer the potential to generate an income from the heat savings, either by increasing the exports of energy and biorefinery products or by reducing the imports of external fuel. Typical technologies and processes that could be considered for a market Kraft pulp mill include increased electricity generation, reduced bark use, lignin extraction, district heating, CO_2 capture, hemicellulose extraction and black liquor gasification with motor-fuel production.

The data collection needed for the pinch analysis that is performed to identify heat-saving measures is usually time-consuming, but not necessarily difficult. However, Step 1 is an essential step of the methodology, since the quality of the optimization results will never be better than the quality of the input data. In a real-world application it is therefore important to integrate the process integration study into the methodological framework proposed in this thesis. One reason for this is to avoid pre-optimization in the selection of promising investment options.

Step 2 – Define the constraints on and effects of combining options

Constraints that express how process integration measures and energy technologies can be combined constitute an important part of the model. The constraints must be based on knowledge about the process and technologies and on the results from the pinch study. With knowledge about how the implementation of one process integration measure affects the conditions of others, the mathematical formulation of the constraints is usually straightforward (see the Section 6.2.3). However, because of the requirements set by the optimization solver, the constraints must be linear, which can make this step more of a challenge.

Step 3 – Gather and compute technological input data

A number of parameter values must be defined in the optimization model for the process integration measures and technology options chosen in Step 1. Input data needed include investment costs and steam savings for the energy-saving measures and energy conversion data and investment cost functions for the energy-conversion and biorefinery technologies.

In the model, an energy conversion parameter is defined as the relation between the output of energy product and steam flow. This parameter is typically calculated based on data such as steam enthalpies, equipment efficiencies and heating values.

Investment costs of process equipment are often given as nonlinear concave functions. Since the optimization model is desired to be linear, a linearization script has been included in the model to automatically approximate such nonlinear functions as piecewise linear functions before the optimization is carried out. In Paper V, an approach that includes uncertainty in the investment cost functions is suggested. This addition to the methodology is described in Section 6.4.

Step 4 – Develop a scenario model for energy market parameters

Input data in the form of energy prices is considered uncertain in the model and is therefore modelled in a scenario-based approach. This was set as the fourth step of the methodology since the first steps determine the products for which prices are required. The modelling of energy market conditions as a scenario tree has shown to be of great importance. It is the part of the methodology that is most novel compared to other methods for evaluating process integration investments. It is also an area that has gone through major improvements as the project has progressed. Because of its central importance and successive improvements, a separate section of this chapter is devoted to discussing the energy market scenario model (see Section 6.3).

Step 5 – Solve the model and analyze the results

The solution to the optimization model is an optimal investment plan with respect to the expected NPV based on the information about the future that is available today. The solution thus contains information about which investments should be made now and at later points in time in different scenarios. The optimal capacity of energy-conversion technologies is also determined, as well as operational decisions for each time period and scenario. The solution can also be analyzed with regard to, for example, the total cost of investments made in each node or the NPV of investments in each separate scenario. The solution value is the expected NPV of the investments.

The solution thus contains information not only about the optimal investment today, but also about the optimal future investments under different energy market conditions. However, these future investments are optimal only under the condition that today's knowledge and assumptions are valid. At the time of a future investment decision, the true outcome of the uncertain parameters up to that point will be known and the knowledge of the future beyond that point will have increased. Before making decisions about future investments, such new information should be incorporated into the model. However, as the results of the case studies illustrate, future investment opportunities will affect the optimal decision of today and are therefore important to include in the current model.

The optimization model is solved by computations performed by an optimization solver. In this project, the solver CPLEX [133] has been used. As further discussed in Section 6.2.4, the computational complexity, and thereby the computation time required to solve the model, depends on the model properties. It is not certain that the model can be solved easily and quickly; the modelling of investments and scenarios will therefore be affected by the requirements of obtaining reasonable computation times.

Iteration

An iterative procedure should be applied to the five steps. By adding or removing investment options and constraints to the model, the effect of different assumptions can be analyzed. Any parameter value can be varied in a sensitivity analysis. This is most important for those parameters that are hard to estimate. The sensitivity of the solution to different assumptions for the probability distribution is especially important to analyze because the probabilities do not have a ‘true’ value but are set to mirror an opinion or belief (see Section 8.4.2). Examples of other assumptions that can be analyzed are the economic assumptions presented in Section 5.2.2. It is sometimes also necessary to reformulate the model through Steps 1–4 in order to reduce the computation times in Step 5.

6.2 Optimization model

In this section, the model for optimization of process integration investments under energy market uncertainty is described. The objective of the optimization is to maximize the expected NPV of the investments. A detailed description of the optimization model formulation is presented in Paper III. Here, an overview of the modelling assumptions, the different components of the model, including variables, objective function and constraints, and the model properties are presented.

The only uncertainties that are incorporated into the basic optimization model concern energy market conditions. Uncertainties in investment cost developments were included in Papers V and VI through an approach based on scenario analysis. This approach does not, however, require any changes in the optimization model itself besides the investment cost parameter which instead of being constant over time is redefined as several parameters taking different values for different years. The model is then solved multiple times with varied values for these parameters (see further Section 6.4). Consequently, the variables, the objective function and the constraints are retained when introducing the investment cost uncertainty.

6.2.1 Decision variables

The modelling of investment and operating decisions in relation to energy market development is based on a few fundamental assumptions that follow the theory of multistage stochastic programming (see Section 5.1.1). First of all, it is assumed that investment decisions are made ‘here-and-now’, which means that they are decided on and implemented before uncertainties in energy prices are resolved and any changes occur. After the uncertainties have been resolved, new ‘here-and-now’ decisions can be made, for example on additional investments, before any further price changes occur. The model also captures that – depending on the investments made – it will be possible to adjust the operation of the plant, for example, regarding the production of electricity or the use of fuel. These operating decisions are also determined by the model.

Since the uncertain energy market parameters are modelled using a scenario-based approach (see Chapter 6.3), the model of the investment decisions can also be naturally represented as a decision tree. As discussed in Section 6.2.4 it is necessary to limit the number of binary variables in the model, in order to obtain tractable computation times. It is therefore important to limit the size of the decision tree, since a new set of binary variables is introduced in the model for each node. In this thesis, a five-year-interval between decisions has therefore been used.

6.2.2 Objective function

The objective of the optimization model is to find the combination of investments that results in the highest expected NPV over all energy market scenarios considered. The objective function can be expressed as to[6]

$$\text{maximize } \mathrm{E[NPV]} \coloneqq -C_0 + \sum_{s\in S} p_s \sum_{t=1}^{T} \frac{C_{t,s}}{(1+r)^t}, \tag{2}$$

where
C_0 = the initial investment cost,
S = the set of all energy market scenarios s,
p_s = the probability for scenario s to occur,
T = the lifetime of investments,
$C_{t,s}$ = the net cash flow in year t for scenario s, and
r = the discount rate.

The same initial investment is required for all energy market scenarios since the first investment decision is made before the values of future energy prices are known. The net cash flow each year is a function of the operating decisions and the energy prices for that period. The operating decisions may concern, for example, the amount of electricity generated in a turbine or the amount of heat delivered to a district heating network. These operating decisions are constrained, for example, by the technology available from earlier investments and their capacities and by mass and steam balances (see Section 6.2.3). The net cash flow of the final year, C_T, should be adjusted for the residual value of the investments (see Paper III, Appendix A, for details and assumptions).

6.2.3 Constraints

The investment and operating decisions are limited by a number of constraints and requirements. Some of these constraints are general and are valid for different applications and case studies, while others depend on the mill and process integration opportunities considered and therefore need to be formulated with respect to prevailing conditions.

The general part of the model consists of mathematical equations and inequalities describing the relations between investment decisions and investment costs, energy savings, and overall mass and energy balances.

Other constraints typically define how process integration measures can be combined, and how they influence each other. These constraints are formulated in the model specifically for each case study. Following here, two basic such constraints that typically arise are presented, where x_m^n is a binary variable that takes the value 1 if measure m has been implemented before node n and the value 0 otherwise:

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[6] The notation here roughly follows the notation used in Papers I and II. In Paper III a more detailed model description is presented, and the notation is more extensive.

- Measure 1 and 2 cannot be combined:
  $x_1^n + x_2^n \leq 1$

- Implementation of measure 1 requires that measure 2 is also implemented:
  $x_1^n - x_2^n \leq 0$

Often, more complex constraints arise because of non-linear relations. Non-linearity can, for example, arise when the effect of combining two process integration measures is not purely additive or when trying to capture, for example, the effect of seasonal variations using annual averages. Because the model is required to be linear, such non-linear relations are reformulated in the model. This, however, often requires several linear constraints and additional, auxiliary, binary variables.

6.2.4 Model properties – integer variables and linear functions

The functions connecting the investment decision variables to energy conversion characteristics and economic data are typically obtained from simulations, experimental data and catalogue selections. These relations can therefore, in practice, not be expressed as analytical functions of continuous variables. The decision variables are instead required to take integer or binary values, expressing a choice between discrete options for which the dependent characteristics can be established in advance.

The introduction of integer or binary variables into the optimization model increases its computational complexity and thus the required solution time, which, in the worst case, grows exponentially with the number of binary variables (see e.g. [134], Chapter I.5). The scenario-based modelling of the uncertain parameters further increases the number of variables in the model, making the model grow combinatorially with a corresponding considerable increase in computing time.

Nonlinearity of the functions describing the relations in the model would further increase the complexity of solving the model, especially since many of the nonlinear functions are typically non-convex. The functions of the final optimization model are therefore desired to be linear. This also makes it possible to use a solver restricted to mixed-integer linear programming (MILP) models. It should be noted that it is possible to avoid non-linearity in the stochastic model despite the presence of recourse stages owing to the formulation of a discrete probability distribution.

To summarize, the optimization model is a multistage, mixed-binary, linear, stochastic programming model. This final MILP model is formulated in AMPL [135] and solved using the commercial MILP solver CPLEX [133]. There are also open-source MILP solvers such as GLPK [136] available that can solve this type of model.

6.3 Energy market scenario model

For the stochastic programming approach, a model describing the uncertainties in the energy market is required. Because of the desired properties of the optimization model, the probability distributions should be discrete and defined over a finite set of scenarios. Furthermore, because of the assumptions made about the decision structure, the scenarios should be modelled as a branched scenario tree. Finally, the time steps in the scenario tree should correspond to the time steps between investment decision opportunities and the total time span which the scenarios cover should be equal the lifetime of the investments.

It is practically impossible to describe the set of all possible future energy market scenarios and to determine their probabilities. Furthermore, the uncertain parameters included will usually depend on the case study. The scenario model should therefore be kept simple so that it is easy to adjust to different conditions. Nevertheless, it is important that the scenarios are realistic. For example, the strong correlation between energy market parameters, such as electricity and fuel prices, must be captured. This can be achieved by using consistent sets of energy market parameters as building blocks in the scenario tree.

To construct consistent sets of energy market parameters, a calculation tool developed by our research group [21, 22] has been used; in its last version [22] it is called the Energy Price and Carbon Balance Scenarios tool (the ENPAC tool). The energy market scenario tool was developed specifically for the evaluation of energy-efficiency investments in energy-intensive process industry. All versions of the scenario tool calculate energy market prices for large-volume customers, based on world market fossil fuel price data and assumed values for energy and climate mitigation policy instruments (see Figure 4).

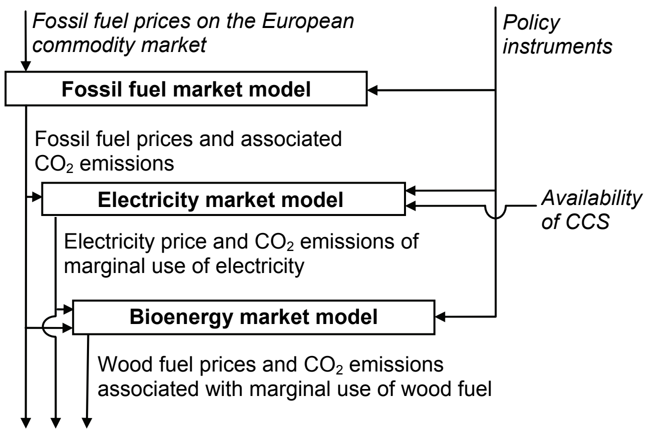

FIGURE 4. Overview of the calculation tool for generation of consistent energy market parameter sets. (Adapted from Axelsson and Harvey [22, p.5, Fig. 2]).

The calculation tool includes pre-defined characteristics of a number of energy-conversion technologies that are potential candidates for marginal electricity production and marginal wood fuel use. Examples of data defined in the tool include annualized investment costs, transportation and operating costs, efficiencies and annual production rates. The user input regarding fossil fuel prices and policy instruments, together with the pre-defined energy-conversion characteristics makes it possible determine the probable marginal energy conversion technologies. This, in turn, yields consistent values for the prices paid by industry for energy carriers such as fossil fuels, electricity and wood fuel. The scenarios and the principles behind the calculation tool are only briefly presented here. For more details, the reader is referred to the report by Axelsson and Harvey [22].

Depending on the case study, different energy products are relevant to include in the scenario model. Specialty products such as lignin are not included in the tool. To obtain prices of such products, it is therefore necessary to make complementary assumptions and further calculations based on the results from the scenario tool. In our case studies, for example, the price of lignin has been valued in relation to the prices of wood by-products. Further assumptions and calculations are often needed also for district heating since its value is strongly connected to the characteristics of the existing production capacity and heat demand in the district heating network.

The article and reports describing the scenario tool [21, 22] also present examples of scenarios calculated by the tool. The input data for these scenarios is based on a literature survey to find realistic ranges of forecasted world market fossil fuel prices and relevant policy instruments. The input data to the scenario models used in this thesis is to a large extent based on this original input data, although adjustments have been made within the identified range of realistic input values, mainly in order to achieve branching in the scenario tree or to adapt the total number of scenarios.

Because this thesis work has progressed in parallel with the scenario tool project, the case studies presented in the thesis use energy market scenario models that are based on different versions of the scenario tool. For Papers II and III, scenario data is calculated using the first scenario tool version [21] while the construction of the scenario models also build on the ideas of Ådahl and Harvey [18]. This 'building block' model is described in Section 6.3.1. For Papers IV, V and VI the scenario model and data are based on ENPAC [22], as described in Section 6.3.2.

6.3.1 The 'building block' model

The first version of the scenario tool calculated energy market prices for only one year [21]. The building blocks thereby constructed are plausible combinations of energy market parameters that may be valid at different periods of time in the future. Following the ideas of Ådahl and Harvey [18, p. 492, Table III], a number of scenarios can be constructed using a few such building blocks ordered to capture the timing of energy market changes. Each scenario building block can be valid in several nodes of the tree. The building blocks were typically selected to represent different ambition levels for CO_2 reductions as described in Table 1, which also presents the specific building blocks included in the scenario models used in Papers II and III.

TABLE 1. Definitions of typical scenario building blocks.

	Building block notation	
Typical scenario building block	Paper II	Paper III
–	I[a]	–
A 'business as usual' evolution of society. Low CO_2 emissions charge.	II	1
A 'moderate change' evolution of society. Moderate CO_2 emissions charge.	III[b]	2A[c] and 2B[b]
A 'significant change' evolution of society. High CO_2 emissions charge	IV[b]	3A[c] and 3B[b]

[a] Representing current Swedish energy market conditions. Not calculated by the scenario tool.
[b] CO_2 capture and storage (CCS) *can* be used with the marginal electricity production if resulting in the lowest production cost.
[c] CCS is *not* assumed to be possible for marginal electricity production.

For each scenario building block, fossil fuel prices (oil, coal and gas) as well as the value of all relevant policy instruments (e.g. CO_2 emissions charge and green electricity certificates) are given as inputs to the scenario tool. For the 'building block'-models, the CO_2 emissions charge was varied while the fossil fuel price was held constant (see Table 2). In Paper II, the price of green electricity certificates was assumed to inversely follow the price of CO_2 emission permits, while this policy instrument was not considered at all in Paper III (see further Section 6.3.3).

TABLE 2. Input data for the scenario building blocks used in Paper II (scenarios denoted by Roman numerals) and Paper III (scenarios denoted by Arabic numerals). The fossil fuel price level is exemplified by the crude oil price.

	Scenario building block					
Input parameters	**I**	**II & 1**	**2A**	**III & 2B**	**3A**	**IV & 3B**
CO_2 emissions charge [€/tonne]	–	26.6	34.6	34.6	42.6	42.6
Crude oil price [€/MWh]	–	31.1	31.1	31.1	31.1	31.1

The prices paid by industry for different energy carriers were calculated using the tool (see Table 3). Further assumptions and calculations were then made to determine the prices for lignin and district heating (see Section 6.3.3).

TABLE 3. Resulting output from the scenario tool for the scenario building blocks used in Paper II (scenarios denoted by Roman numerals) and Paper III (scenarios denoted by Arabic numerals).

	Scenario building block					
Price parameters [€/MWh]	**I**	**II & 1**	**2A**	**III & 2B**	**3A**	**IV & 3B**
Electricity	38.6	57.3	63.0	60.8	68.8	61.9
Wood by-products (e.g. bark)	13.0	15.2	18.0	18.0	20.7	20.7

Based on the scenario building blocks, a number of possible development paths – scenarios – were constructed. Since the building blocks are chosen to represent different levels of the CO_2 emissions charge, the scenarios should be constructed to represent different assumptions on the speed of the increase of the CO_2 charge and its final level. As examples of how this can be done, Figure 5 shows the scenarios used in Paper II and Figure 6 those of Paper III.

All parameters are assumed to be constant for periods of five years, which also determines the length of each stage in the scenario tree and the decision model. The total calculation horizon is 30 years, which also corresponds to the economic lifetime of the investments.

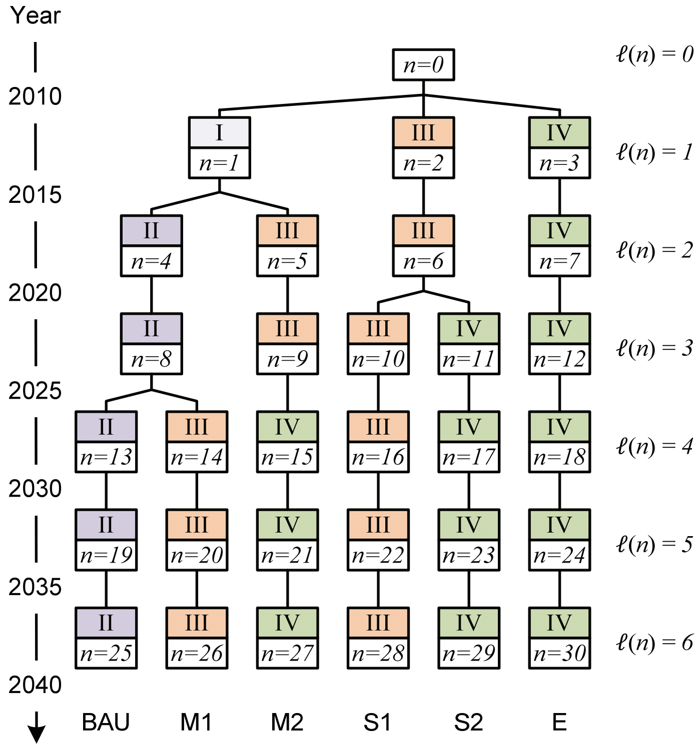

FIGURE 5. The scenario tree used in Paper II, composed of four scenario building blocks representing an increasing attention to climate issues.

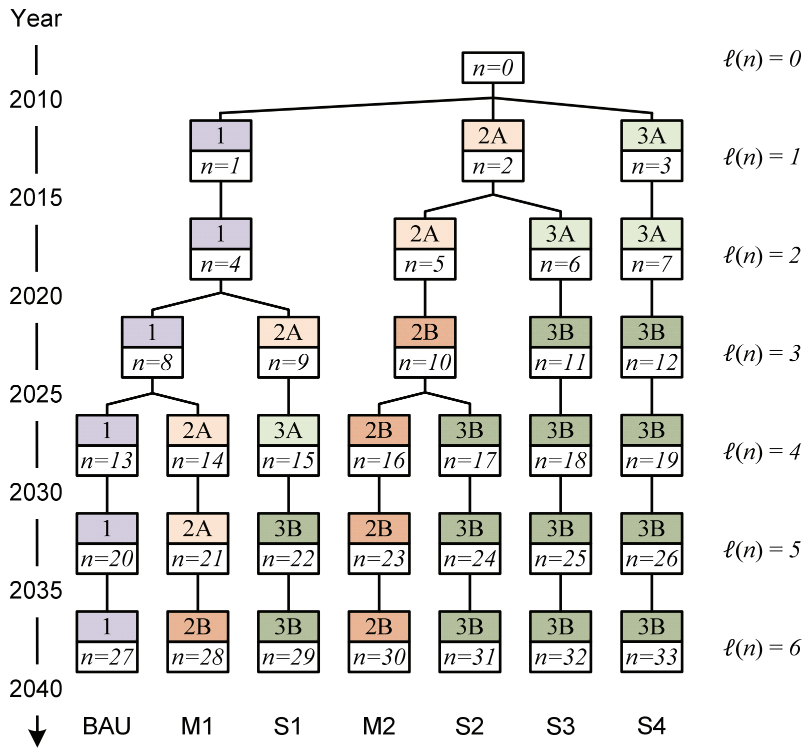

FIGURE 6. The scenario tree used in Paper III, composed of five scenario building blocks representing an increasing attention to climate issues.

6.3.2 New ENPAC-based scenario model

As work progressed with the optimization methodology, a number of issues that could be improved in the scenario model were identified. Most importantly, this regarded the way timing was considered. Typically, a high CO_2 emissions charge would not be the same in 2020 as in 2040. Furthermore, variations in fossil fuel prices had not been considered in the early scenario tree models although the possibility was included in the scenario tool. The reason was mainly that the ‘manual construction’ of the scenario tree from the building blocks made it difficult to systematically handle the greater number of building blocks that would have been the result of including multiple levels also for this parameter. However, the work on the scenario tool also continued and it was developed into the new version called ENPAC [22]. Besides general updates of data, the main novelty was the potential to consider different years, and work was also carried out to identify realistic input data for fossil fuel prices and policy instruments for the different years.

Input data for our new scenario tree model, which now includes different levels also of fossil fuel prices, is based on the input data used for the example scenarios in the ENPAC report [22]. However, these original example scenarios were intended to set out some upper and lower limits of possible future energy market conditions. Our model should include the most probable scenarios and therefore intermediate values were also added.

In addition, the scenarios with the lowest and highest values for the CO_2 emissions charge were also adjusted. For the high level, the linear increase over time was changed to an exponential increase with the same final value in year 2040, thereby following the assumptions for the other scenarios. The lowest level was assumed to have a low probability and was therefore removed.

Further adjustments were made, mainly to obtain multiple branching nodes in the scenario tree. The difference between the original input and the adjusted scenario tree input is illustrated for the crude oil price in Figure 7. Coal and gas price scenarios were derived in the same way. Figure 8 shows the original and adjusted CO_2 scenarios.

The main assumptions used for the remaining input data to the scenario tool are listed below.

- The support for electricity production from wood fuel is constant at €20/MWh_{el}, which is according to standard input used for the example scenarios presented in the ENPAC report [22] (see also Section 6.3.3).
- CO_2 capture and storage is assumed to be available for the price-setting electricity production technology at the earliest 5 years after becoming the most cost-effective alternative for electricity production.
- The support for production of renewable transportation fuel is, in accordance with standard input, set to represent a harmonization of the CO_2 emission trading scheme over all sectors including the transportation sector. Since the prices of transportation fuel are not used in this thesis, this assumption only affects the willingness-to-pay for wood fuel. The result is that for a majority of scenarios, the marginal user – and price-setter – of wood fuel is co-firing in coal power plants.

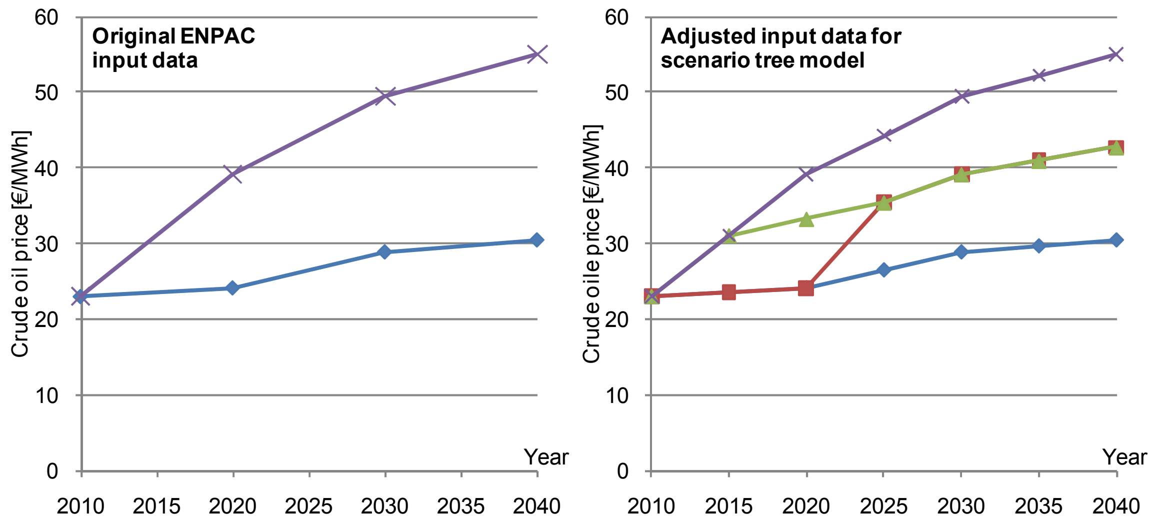

FIGURE 7. Fossil fuel price scenarios exemplified by the price of crude oil. Left: original ENPAC scenario data. Right: adjusted scenario data used in the stochastic programming model.

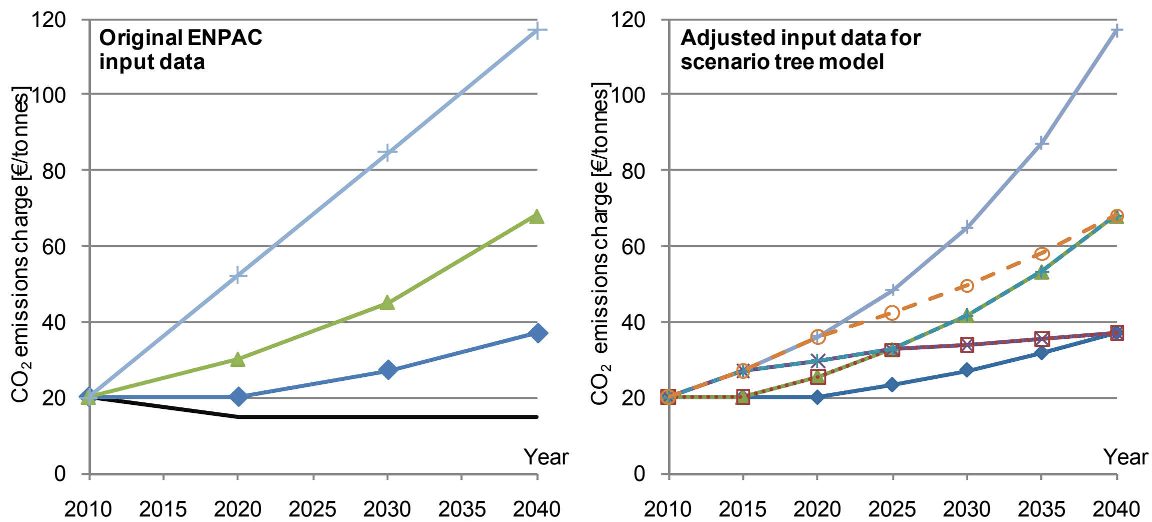

FIGURE 8. Scenarios for the CO_2 emissions charge, i.e., the price of CO_2 emission permits. Left: original ENPAC scenario data. Right: adjusted scenario data used in the stochastic programming model.

By combining each of the seven CO_2 charge scenarios with each of the four fossil fuel price scenarios, and applying the above assumptions, a resulting 28 scenarios were obtained for which electricity and fuel prices for industrial customers were calculated using the ENPAC tool. The resulting scenario tree has 120 nodes which can be compared to around 30 for the 'building block' models. The computation time required to solve the optimization model thereby increases drastically (from about one minute to several hours). The computational performance is, however, still acceptable and the representation of probable future developments of the energy market is significantly improved. Examples of the resulting prices of electricity and bark given as outputs from the scenario tool are shown in Figure 9.

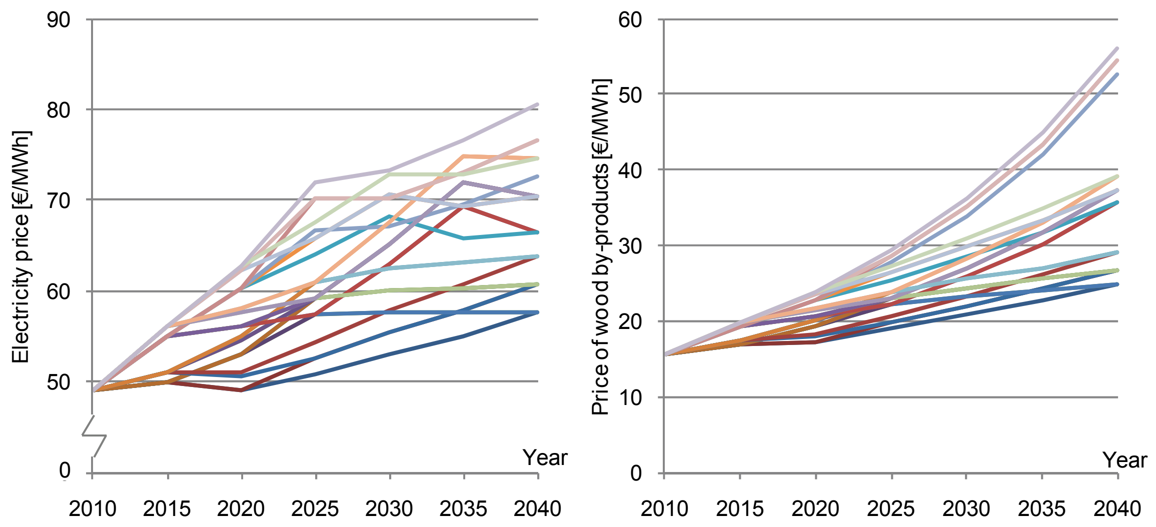

FIGURE 9. Output scenario prices. Left: Electricity price (with the value of the green certificates excluded). Right: Price of wood by-products (e.g. bark).

6.3.3 Assumptions for output from the scenario tool

In addition to the differences due to updates in the scenario tool, the examples differ with respect to the assumptions made for products not included directly in the scenario tool. These assumptions include the price setting for lignin and district heating and, to some extent, the conditions for support to renewable electricity production onsite at the mill.

District heating price

The ENPAC tool enables the calculation of a price span for district heating. This is done by setting maximum price in relation to the price of heat from a local gas boiler and setting the minimum price in relation to the price of heat from a coal CHP plant. These represent common heating technologies in Europe. The resulting price span is, however, broad and no consideration is given to local conditions with regard to heat production technologies actually present in the relevant district heating network or to the heat-load duration curve. The price of district heating for each case study was therefore chosen to represent realistic conditions for a local district heating network.

There are a number of alternative price setting principles for district heating [137]. The price of the delivered heat in the scenario model should, obviously, be set according to the price setting principle relevant for the studied pulp mill. Since the mills considered in our case studies are fictional (i.e. not exactly representing any real mill), assumptions must be made about a relevant price setting principle. One realistic assumption is that the price is set in relation to the alternative production cost of district heating. In Sweden, which is one of the countries with the largest production of chemical pulp worldwide, and where all but one of the case study mills are located, there is a large share of biomass in the district heating sector. When relevant in our case studies, the price of district heating was therefore set in relation to the biomass price, a parameter which is calculated in ENPAC. Table 4 presents the assumption made about the district heating price in each case study.

TABLE 4. Assumed price setting for district heating in the case studies.

Paper - Example	District heating price assumption
Paper II and IV	75% of the alternative production cost Alternative production: Existing biofuel boiler
Paper III	District heating is not considered
Paper V and VI	85% of the alternative production cost Alternative production: New biomass CHP plant[a]

[a] Assumed depreciation with capital recovery factor of 0.2

Lignin price

Lignin extraction is an emerging technology and no market price for lignin has yet been established. Depending on the assumed use of lignin as a high-grade wood fuel or a raw material for chemicals or materials, the value should be set in relation to the wood-fuel price or, for example, the oil price. In our case studies different assumptions about the value of lignin were made depending on the purpose of each specific study. Table 5 summarizes these assumptions.

TABLE 5. Assumed price setting for lignin in the case studies.

Paper - Example	Lignin price assumption
Paper II and III	150% of the price of wood by-products
Paper V and VI	Equal to the fuel oil price
Paper IV	Base price: 135% of the price of wood by-products After 2015 in half of the scenarios: The fuel oil price + €10/MWh

Electricity certificates

The general level of support to biomass fuels used for electricity production in Europe affects the European market price for wood fuels. In different countries this support is given as electricity certificates, feed-in tariffs or other policy instruments. A generalized support level is included in the input data to the scenario tool (see e.g. Table 2).

In addition, the specific support scheme for green electricity in the country in which a mill is located will have a direct effect on the price of renewable electricity generated at the mill. All of the studied model mills, except the one in Paper III, are assumed to be located in Sweden where there is a system of green electricity certificates. For renewable electricity, the value of these green certificates was added to the market electricity price for the first 15 years after the investments were made to achieve the electricity generation capacity [138]. Since the electricity generated at the mills is based on wood fuel it is eligible for green electricity certificates.

In our case studies different assumptions were made about the value of the electricity certificates and about the countries in which the studied mills are situated (and consequently about the existence of a certificate system). Furthermore, the 15-year-limit on the right to receive electricity certificates was not considered in the first case studies. The assumptions about the electricity certificates are summarized in Table 6.

TABLE 6. Assumptions made regarding the value of green electricity certificates.

Paper - Example	Assumption regarding green electricity certificates
Paper II	Certificates are granted to electricity generated at the mill at all times. Values in scenario building blocks [€/MWh]: I:21.7, II:16.0, III:10.6, IV:5.3
Paper III	No green electricity certificates are considered. (Mill is not assumed to be located in Sweden)
Paper IV, V and VI	Certificate value is constant at 20 €/MWh, but only granted during the first 15 years after the turbine investment.

As seen, the assumption made in Paper II – that the certificate value will decrease as CO_2 charges increase – differs considerably from the assumption made in Papers IV, V and VI in which the certificate price is assumed constant. The assumption made in Paper II is motivated by the combined effect of the emissions trading scheme and the electricity certificate quota system (see e.g. [139] for an analytical description of the relation between the certificate price and the emission permit price). The exact price levels chosen equal the standard input used for the example scenarios constructed by the scenario tool [21]. In the Nordic electricity system, with large shares of hydro and nuclear power, the actual quantitative effect of the emissions trading scheme on the certificate price has, however, been shown to be limited (see e.g. [139, 140]). The assumption made in Papers IV, V and VI was therefore changed to represent a constant certificate price level. The value of 20 €/MWh has been estimated as a European average for green electricity support and was therefore assumed for greater generality of the results. This price is also on a historically reasonable level for the Swedish electricity certificate system.

The assumption about the electricity certificate price is important since it has a major influence on the profitability of electricity production. For further application of the methodology proposed in this thesis to Swedish mills, this is probably one of the most important parameters to study. However, the assumption does not have any direct influence on the methodology development which is the main objective of the thesis. Furthermore, the assumption is of direct interest only for applications in countries with a similar quota system. In Europe, feed-in tariffs are more common as support to renewable electricity.

6.3.4 Scenario probabilities

For the stochastic programming model, the probability of each of the scenarios must be estimated. However, the uncertain parameters considered here, that is, the energy market parameters, are – on a long-term time scale – not expected to vary according to historical trends only. The energy market will probably be affected also by strategic climate policy decisions and/or changes in the reliability of fossil fuel supply. This would result in energy market prices that not only fluctuate according to market forces, but also change due to a successive restructuring of the energy sector. While the rate and timing of these changes are uncertain, the probability of different outcomes is also uncertain and not straightforwardly based on historical data, statistics or probability theory.

Nevertheless, a probability distribution can be assumed to represent the decision-makers' opinion or beliefs regarding the future development of the energy market (see e.g. [141] for a related study in which probabilities are set as relative weights based on expertise and preference). It is, however, important to remember that the probability distribution assumed is uncertain in itself. The sensitivity of the solutions with regard to this assumption should therefore be analyzed. As shown in Papers II and III a sensitivity analysis can be carried out in a straightforward way within the framework of the methodology (see Section 8.4.2). Even if it turns out that the solution is sensitive to differences in the probability assumption, the results of the analysis can show which scenario probabilities are most important for the decision-maker to take a stand on.

In our studies, the main objective is to illustrate the use of the optimization methodology. For simplicity, the probabilities of all energy market scenarios included in the optimization model have therefore been assumed to be equal as a base case assumption.

6.4 Investment cost uncertainty

In Paper V, the methodology proposed in Paper I was developed to include uncertainty in investment costs in addition to energy market parameters. Although there is usually uncertainty regarding the investment costs of all technologies, the uncertainty is assumed to be especially high for new, emerging technologies. Our model assumes uncertainty for technologies that have not yet been commercialized and proven at full scale.

Since the system delimitation assumed in this thesis is set around one specific mill, the accumulated installed capacity of a technology cannot be a variable in the optimization model. Unlike in a learning curve approach, an exogenous modelling of technological change is therefore required. Furthermore, the cost reductions must be modelled as dependent on time, which is not the case if they are modelled using learning rates (see e.g. [142]). Moreover, the technologies studied in this thesis (e.g., CO_2 capture and lignin separation) can be described as large, non-modular plants that require substantial construction on-site and are not yet commercial. This is typically not characteristic of technologies for which learning rates are best applied (see e.g. [143–145]).

Instead, the problem was approached in a way resembling that of Fuss and Szolgayová [60] and Zhou et al. [62] and different scenarios were modelled for cost reductions. However, since the methodology proposed in this thesis has another purpose than the one developed in the cited studies and does not apply a real options approach (see Section 5.1), there are justified differences regarding how the scenarios are modelled.

Our model is built around data that is often available for an emerging technology studied in research and development projects, that is, estimations of future costs of the Nth plant (that is, for the technology at a mature stage). However, this cost will only be reached if the technology actually reaches a mature stage, and maybe not even then. We therefore propose the modelling of scenarios that represent developments of the investment cost that vary with regard to both the timing of cost reductions and the levels of the investment cost. Section 6.4.1 describes these scenarios and Section 6.4.2 presents the proposed approach for using these scenarios in combination with the original methodology.

6.4.1 Scenarios for the uncertain investment cost development

The lack of historical data, relevant probability functions, or other relevant, objective data to base the modelling of the cost development on necessitates a use of more subjective data. These are typically cost estimations assuming that the technology will in fact reach a mature stage, or expert opinions about the time remaining for demo-scale operation before commercialization is possible. These estimations often yield a range of probable cost developments and therefore demand the modelling of a number of scenarios. The aim of modelling the cost of the emerging technology should be to roughly capture different relevant opinions and beliefs about the future development without suggesting a level of detail and degree of accuracy that do not really exist. We therefore propose the use of only a few scenarios representing different timings and levels of cost reductions.

The time steps of the cost development scenarios must coincide with the time steps used in the stochastic programming model for investments and energy market scenarios. Owing to the long time steps used in our model, the investment cost is required to be estimated only at a few points in time, making it convenient to model the cost development using discrete values. As a result, the scenarios can represent different timings and levels of cost reductions without the need to conform to a specific function for technological learning. This way, various assumptions about the progress of cumulative technology experience can be represented, thereby enabling a time-independence of technological learning.

The scenarios are proposed to be modelled with one base cost level and one or a few higher cost levels. The base cost level could typically represent the investment cost estimated for the so-called N^{th} plant, that is, the cost normally assumed for the new technology at a mature stage. A higher cost level could, for example, represent a cost assumed at an early stage in the commercialization process. Market introduction is assumed to be possible at different points in time at either of the investment cost levels, or not at all. Unavailability of the technology on the market is represented in the model as a significantly higher investment cost; in our case studies, a level 100 times higher than the base cost has been used.

As an example of a cost development scenario model, Table 7 presents the six scenarios used in Papers V and VI for the cost of a lignin separation plant. For this technology, the assumption is that market introduction might happen in 2015 or 2020 at either of two cost levels. Paper V also proposes a sensitivity analysis of the higher cost level assumed within the cost development scenarios.

TABLE 7. Investment cost scenarios for the lignin separation plant.

Scenario	**2010**	**2015**	**2020**	**2025**	**2030**	**2035**
Low15	–	L	L	L	L	L
Low20	–	–	L	L	L	L
High15	–	H	H	H	H	H
High20	–	–	H	H	H	H
HighLow	–	H	L	L	L	L
Never	–	–	–	–	–	–

–: Unavailability
L: Low cost / base cost level = N^{th} plant cost
H: High cost / Higher cost level = 1.5 L

6.4.2 Including the cost development scenarios in the optimization model

If the cost development uncertainty is incorporated into the existing optimization model in a stochastic programming approach, a combined scenario tree of both energy market and cost development uncertainty would be required. With the 28 energy market scenarios and six cost development scenarios assumed in Papers V and VI, the combined scenario tree would consist of 168 (28 × 6) scenarios and 664 nodes, as illustrated in Figure 10.

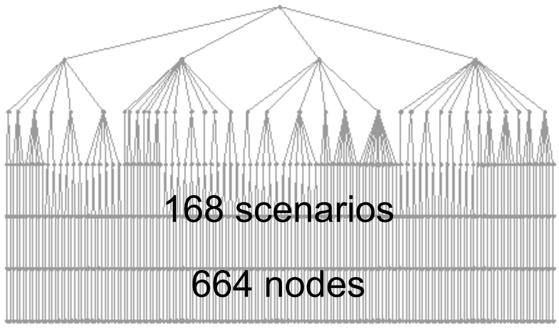

FIGURE 10: Combined scenario tree

Each scenario tree node is associated with a set of decision variables, and the solution time for the optimization model grows quickly when increasing the number of binary variables. A few test runs also indicated long solution times as the optimal solution was not identified after 24 hours. The stochastic programming approach was therefore judged unrealistic for the cost development uncertainty while at the same time stochastic programming was used for energy market uncertainties. The cost development uncertainty is, instead, proposed to be studied by using scenario analysis.

The scenario analysis starts with the identification of promising, alternative investment packages. A couple of investment packages can be identified as the optimal solutions to different cost development scenarios. However, not all feasible, promising solutions can be found this way, and other investment packages might be the ones that are optimal overall even if they are not optimal for any single scenario. It is therefore always a good idea to identify other investment alternatives also based on experience from working with the model and the mill. The E[*NPV*] of the identified investment packages is then compared for different cost development scenarios.

6.5 Long lead times

Investments in process integration for pulp mill biorefineries are not quickly implemented. Time is needed for detailed analyses of the planned, new technologies, processes and system solutions as well as for contracting, construction and start-up. This results in long lead times from the first decision to invest in a certain technology pathway until its actual implementation or installation. In Paper VI the methodology proposed in Papers I and V was further developed to consider the lead-time aspects of long-term decision-making.

A basic assumption of the proposed approach is that it is already too late to decide about investments that should be implemented today. The first investment opportunity in the model is therefore in five years. By the addition of constraints to the optimization model, only investments planned for today will be possible to implement in five years. Finally it is assumed that it is not possible to plan for all investments that might be of interest. This way, although costs associated with the lead time are not explicitly accounted for, they are implicitly considered in the proposed modelling approach.

Different planning alternatives are identified by optimizing the investment five years from today for each cost development scenario. Further alternatives can also be added based on experience from working with the model and the mill. A matrix can then be constructed that indicates which investments will be possible to implement depending on what has been planned for. A general illustration of such a matrix is shown in Figure 11.

		Possible to implement 2015				
		Technology 1	Technology 2	Technology 3	Technology 4	Technology 5
Plan 2010	Investment package 1	X	X			
	Investment package 2		X	X		
	Investment package 3		X		X	
	Investment package 4					X

FIGURE 11. Generic matrix for investment planning.

Each of the planning alternatives implies the inclusion of constraints in the optimization model according to the matrix. These constrains disable investment at the first investment opportunity in technologies that have not been planned for. Finally, for each planning alternative, the optimization model, with the additional constraints, is solved to get the value of the investment plan in each cost development scenario. Thereby the results of alternative investment plans considering the initial lead time of five years can be analyzed, and the best one possibly identified.

7 Case studies – Overview and results

A number of case studies were performed in this project. This chapter gives first an overview of the case studies and describes the models and assumptions used (Section 7.1). In Section 7.2, the main results of the optimization performed for each case study are presented.

7.1 Descriptions of the case studies

This section gives an overview of the case studies in the project. First, a summary is presented of the mills, process integration measures, technologies and scenarios used in each case study. Then, each case study is described in a separate section.

Each case study was chosen for the purpose of clearly illustrating the new methodological aspects introduced in each paper. Therefore, the results as such, with regard to an optimal investment plans, have not been the main interest. Many times, assumptions and parameter values have been chosen with regard to how the methodology is best illustrated. Therefore, they might not be the most interesting from the mill's perspective. The values and assumptions chosen are, however, fully possible and realistic.

All case studies are taken from the pulp and paper industry and all mills studied are market Kraft pulp mills. Table 8 indicates in which of the papers of the thesis the case studies occur and summarizes their main differences with regard to mill types and energy market scenario models used.

TABLE 8. Summary of case study characteristics.

Case study	Paper	Mill	Energy market scenario model
1	II (Report[a])	Model mill	Building block
2	III	Hypothetical mill	Building block
3	IV	Real mill	ENPAC-based
4	V-VI	Model mill	ENPAC-based

[a] The case study is also described in a detailed report of the mathematical model [1].

Within this thesis project, which is focused on the methodological approach, there has not been room for any detailed process integration studies. Instead, the case studies are based on previous studies conducted by our research group investigating the potential for process integration and various energy and biorefinery technologies in Kraft pulp mills [27, 74–79].

In all case studies, typical steam-saving measures include: solving pinch violations, modernizing the evaporation plant, installing more efficient equipment and avoiding venting steam to atmosphere. In Case study 2, however, the steam saving measures are hypothetical and have been defined only by the amount of steam saved and the investment cost. The energy-conversion technologies included in each case study are listed in Table 9.

TABLE 9. Energy-conversion technologies included in the case studies.

Case study	Energy-conversion technologies included in the model
1	• New back-pressure turbine • Condensing turbine • Lignin extraction (lignin priced as wood fuel) • District heating from low-pressure steam and from excess heat both with and without the need for heat pumping
2	• Existing back-pressure turbine • Condensing turbine • Lignin extraction (lignin priced as wood fuel) • Bark boiler
3	• Existing back-pressure turbine • Condensing turbine • Lignin extraction (lignin priced either as a wood fuel or as an added-value product, but then requiring an upgrading process) • Bark boiler • District heating from low temperature excess heat
4	• Existing back-pressure turbine • Low-pressure turbine with or without combined production of district heating • District heating from low-pressure steam and from excess heat both with and without the need for heat pumping • Either CO_2 capture or lignin extraction (lignin priced as fuel oil) is included in two different examples

Short descriptions of each case study are provided below. For input data, the reader is referred to the appended papers of the thesis.

7.1.1 Case study 1 – Production increase

In this case study different options for the process integration of a pulp mill in connection with a planned production increase were investigated. The studied mill is the market type mill from the research project FRAM (Future Resource Adapted pulp Mill) which is a model mill representing an average Scandinavian mill. Data is taken from [74–76].

One of the bottlenecks for the planned production increase in the mill is the recovery boiler and two options for removing this bottleneck were considered. The alternatives were to invest in a Recovery Boiler Upgrade (RBU) to increase the capacity of the recovery boiler or in a Lignin Extraction Plant (LEP) to decrease its load. In this work, lignin was assumed to be priced as a low-grade wood fuel. Electricity generation and district heating opportunities were also considered.

7.1.2 Case study 2 – Simplified example for the illustration of the methodology

This example was originally developed to illustrate the proposed methodology in a comprehensive way. The main grounds for data selection were to fit the general formulation of the optimization model while still representing the possibility to use specific case study constraints, and simultaneously, clearly illustrate the advantage of the stochastic programming approach. The mill and especially the process integration data are therefore hypothetical although to some extent the same data is used as in Case study 3.

The main investment choice regarded that between lignin extraction and electricity production. Here, the mill also had the possibility to decrease the load on its bark boiler and export bark. This would not require any investment. However, the value of bark is quite low, and it is typically better to make investments to enable energy exports in the form of a more valuable energy carrier such as electricity[7]. The price of lignin, on the other hand, is higher than that of bark, but only in a few energy market scenarios is it high enough to motivate investment in a lignin extraction plant instead of a turbine.

7.1.3 Case study 3 – Lock-in effects

For Case study 3, mill data was taken from [79]. Data for process integration opportunities was adapted from [79] and [74]. In this case study, energy savings achieved through process integration could enable either electricity generation, district heating deliveries or lignin extraction. The extracted lignin is currently valued as a wood fuel, but in the future it is possible that the lignin can be further processed into products that can be valued as material or chemicals. The process for upgrading of lignin would require heat, and thereby reduce the amount of heat available for external deliveries in the form of district heating. The attractiveness of lignin extraction compared to district heating and electricity production would, however, increase owing to the higher value of the lignin product. The purpose of the study was to investigate the lock-in effects of a district heating contract if the possibility to receive a higher value for the lignin was considered.

7.1.4 Case study 4 – Including uncertainty in technology development

This is another example of a process integration study of the same pulp mill used in Case study 1, but here some investments were assumed to already be implemented. One slightly changed option for combined production of electricity and district heating was also added. In addition to the technologies considered in Case studies 1 and 2, CO_2 capture was also included in one example. However, neither CO_2 capture nor the lignin extraction technology was assumed to be available for investment as early as today. Furthermore, the future investment cost of the emerging technology was considered to be uncertain. This case study was used to illustrate a new approach for the modelling of uncertain technology development using cost development scenarios.

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[7] Because of the simplifications made in this example, the realism of some results can be argued, for example, the profitability of wood fuel-based electricity production in a condensing turbine. Examples of simplifications made are that seasonal variations and minimum load requirements on the boiler are neglected.

In the main example of Paper V, lignin extraction represented a possible future change. The main choice for the pulp mill today turned out to be whether investment should be made in a heat pump or not. The heat pump would be used to lift low-temperature heat to a temperature level sufficient for district heating deliveries. Without the heat pump, the low-temperature heat would be available for internal use, typically enabling lignin extraction. In this case study, district heating deliveries were modelled to be possible only if the mill entered a long-term contract. In Paper VI this example was extended to include the consideration to long lead times.

7.2 Summary of the main results from each case study

The results presented in this chapter are the main results – the optimal solutions, and the solution values – from each individual case study. Results common for several or all case studies and a general discussion of the results are presented in Chapter 8. In order to facilitate the interpretation of the results, a short comment on the output from the optimization model is presented in Section 7.2.1.

7.2.1 Solutions and solution values

The solution to the optimization model is an investment plan indicating the optimal investments today and in the future, with the optimal future investments depending on which scenario is realized. The optimal solution includes also the optimal operation of the energy technologies invested in so far. Although the methodology allows the optimization of future investments, the actual decisions about these future investments should not be made until more information about the development of the energy market has become available. Consequently, the most interesting information from the optimal solution is the optimal investment today.

The value of the optimal solution is the expected NPV of the optimal investment plan. However, it is often useful to compare the value of the optimal solution under uncertainty with the value of alternative investment plans under different energy market scenarios. The alternative investment plans can either be identified by a scenario analysis, by which the optimization model is solved with 100% probability for one scenario at a time, or from experienced assumptions.

While the measure of the solution value – the expected NPV – is an adequate objective in the optimization model, it is not always an adequate value for illustrative comparison of solutions since significant differences tend to end up in small numbers. This is due to the weighting with respect to both scenarios and time. The time periods are weighted together taking into account the time value of money for calculating the NPV, and the scenarios are weighted together by their probabilities for calculating the expected value of the NPV. Many times, it is therefore more relevant to show a difference between the solution values for separate scenarios in the time periods when the differences are most pronounced. This can be achieved using annual net profit (ANP), which can be calculated for each time period and scenario from cash flows available from the optimization results.

7.2.2 Case study 1 – Production increase

All in all, four alternatives for the initial investment were identified using scenario analysis and optimization under uncertainty in Case study 1 (see Table 10). Investment alternative I2 was identified as the optimal solution for five realistic probability distributions[8]; it was also identified as an optimal solution using scenario analysis. All investments were made immediately in each of the identified investment plans.

TABLE 10. Results for Case study 1. Main alternatives for the initial investments. I2 is the optimal solution under uncertainty.

Investment alternative	Description of the investment package (Only distinguishing characteristics are presented)
I1	Recovery boiler upgrade (RBU). No lignin extraction plant (LEP). Only focus on electricity generation and district heating (DH).
I2*/I3/I4	No RBU. Minimum/Moderate/Maximum LEP capacity. High/Moderate/Low focus on electricity generation and DH.

* Optimal solution under uncertainty

Figure 12 shows a comparison of the investment alternatives for different realizations of the energy market scenarios which were illustrated in Figure 5.

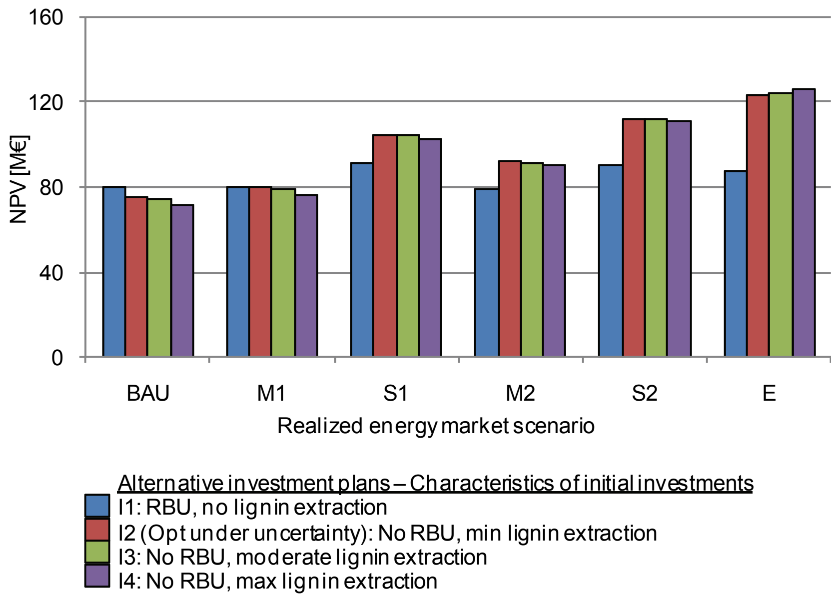

FIGURE 12. Results for Case study 1. NPV of the optimal solution under uncertainty (I2) and of three alternative solutions (I1, I3 and I4) for different realizations of energy market scenarios (see Figure 5 for scenario definitions).

The alternative I1 is shown to have a significantly poorer performance than the other investment alternatives in some scenarios. The differences in NPV between the other

[8] In addition to a uniform probability distribution, four distributions with scenario probabilities ranging from 5%–30% for individual scenarios were tested.

three alternatives are, however, very small, making it difficult to determine – from the results in Figure 12 – which one is the best overall. The stochastic programming approach identified investment alternative I2 to be optimal for all realistic probability distributions considered. However, any of the alternatives I2–I4 would be a good option, considering the negligible differences in NPV in each scenario.

The results from Case study 1 are further discussed in the following sections with regard to lock-in effects in Section 8.2 and with regard to robustness in Section 8.4.

7.2.3 Case study 2 – Simplified example for the illustration of the methodology

In Case study 2 the optimal solution identified using the stochastic programming model could not be identified as optimal for any single scenario (see Figure 6 for definitions of the scenarios used). For the deterministic models – with 100% probability for one scenario and 0% for the others – the optimal initial investment was either to invest in a large turbine or in lignin extraction. The optimal solution under uncertainty, assuming a uniform probability distribution was, however, to invest in a small turbine and utilize the potential to reduce the load on the bark boiler. Figure 13 illustrates this investment decision tree that is optimal under uncertainty.

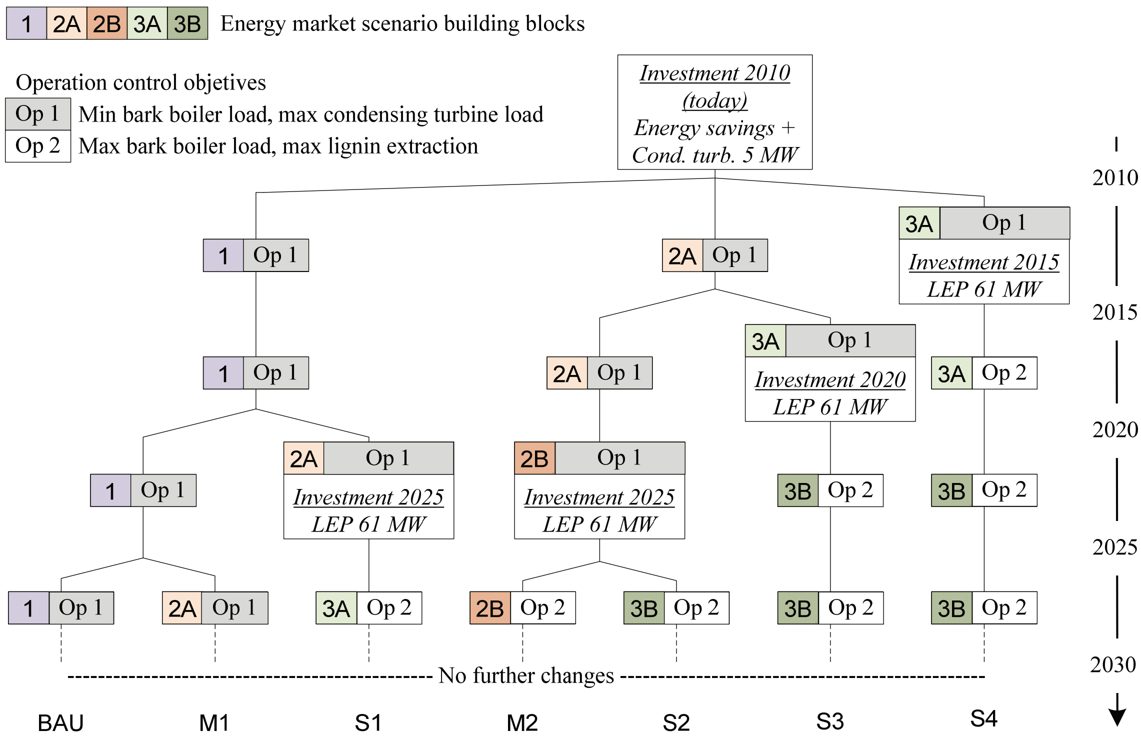

FIGURE 13. Optimal solution for Case study 2 assuming a uniform probability distribution. The decision tree illustrates the optimal investment decisions as well as the optimal operating strategies (see Figure 6 for scenario definitions).

As shown in Figure 13, the optimal solution implies that the decision to invest in lignin extraction is postponed until (when and if) it becomes profitable. Furthermore, by investing only in a small turbine, the mill avoids extensive investment in turbine capacity that will later be left unutilized if lignin extraction is implemented. The bark savings enables earning revenue from the energy savings in the absence of the larger turbine.

In Paper VII, five alternatives for the initial investment (I1–I5) were analyzed, including the optimal investment under uncertainty (I4). These are described in Table 11.

TABLE 11. Description of the five investment alternatives analyzed in Case study 2.

Investment alternative	Description of the initial investment package (Only distinguishing characteristics are presented)
I1	Large condensing turbine, no LEP, ambitious energy savings
I2	Large LEP, no condensing turbine, ambitious energy savings
I3	No condensing turbine, no LEP, modest energy savings
I4	Small condensing turbine, no LEP, ambitious energy savings Optimal solution under uncertainty for uniform probability distribution
I5	Small condensing turbine, small LEP, ambitious energy savings

A comparison of the investment alternatives for different realizations of energy market scenarios is shown in Figure 14.

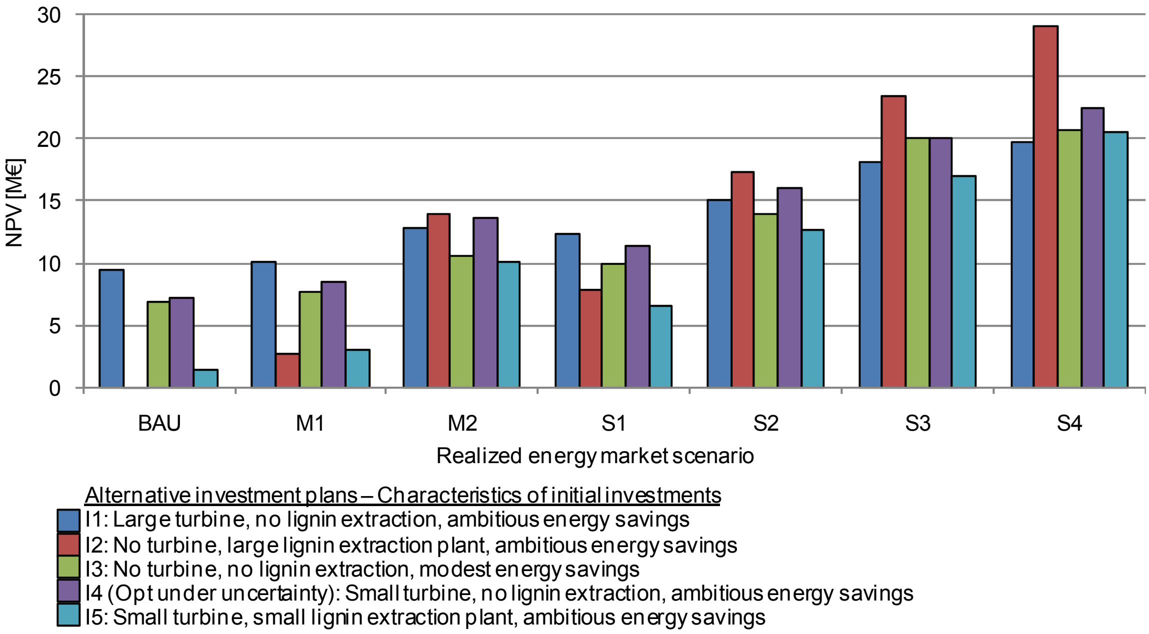

FIGURE 14. Results for Case study 2. NPV of the optimal solution under uncertainty (I4) and of four alternative solutions (I1, I2, I3 and I5) for different realizations of energy market scenarios.

The results from Case study 2 are further discussed with regard to the value of future investment opportunities in Section 8.3 and with regard to robustness in Section 8.4.

7.2.4 Case study 3 – Lock-in effects

In Case study 3, the production of district heating is a very attractive option owing to favourable district heating prices. The production of district heating can be straightforwardly combined with electricity production in a condensing turbine. Lignin extraction, which is also considered, can compete only at very high lignin prices. If lignin is valued as a wood fuel, such high lignin prices are assumed to be present only in a few energy market scenarios and not at all within the nearest future. Initial investment in district heating and in a condensing turbine therefore constitutes the optimal solution for each energy market scenario. Consequently, this is also the optimal solution for the stochastic programming model when lignin is valued as a wood fuel only.

However, the possibility to receive a higher value for lignin was also considered in Case study 3. In addition to the 28 energy market scenarios in which lignin is valued as a wood fuel, another 28 scenarios were included in the model to represent a higher lignin price that could be achieved beginning in the year 2015. When considering this possibility, the initiation of a district heating cooperation risks leading to a lock-in situation if it demands a long-term contract. To investigate the cost of such a lock-in situation, the optimal solutions obtained for two different assumptions for district heating were compared:

(A) District heating can be delivered, but there is no requirement for a long-term contract;
(B) A 15-year district heating contract is assumed.

Figure 15 shows the results by illustrating the difference in ANP for the 56 scenarios with and without a lock-in situation, that is, the difference between the optimal solutions for (A) and (B). By illustrating the increase in ANP, the difference between the two assumptions is highlighted instead of the variations in ANP over the scenarios that cannot be influenced by mill decisions. Figure 15 thus shows the value of avoiding the lock-in situation of a long-term district heating contract in different scenarios.

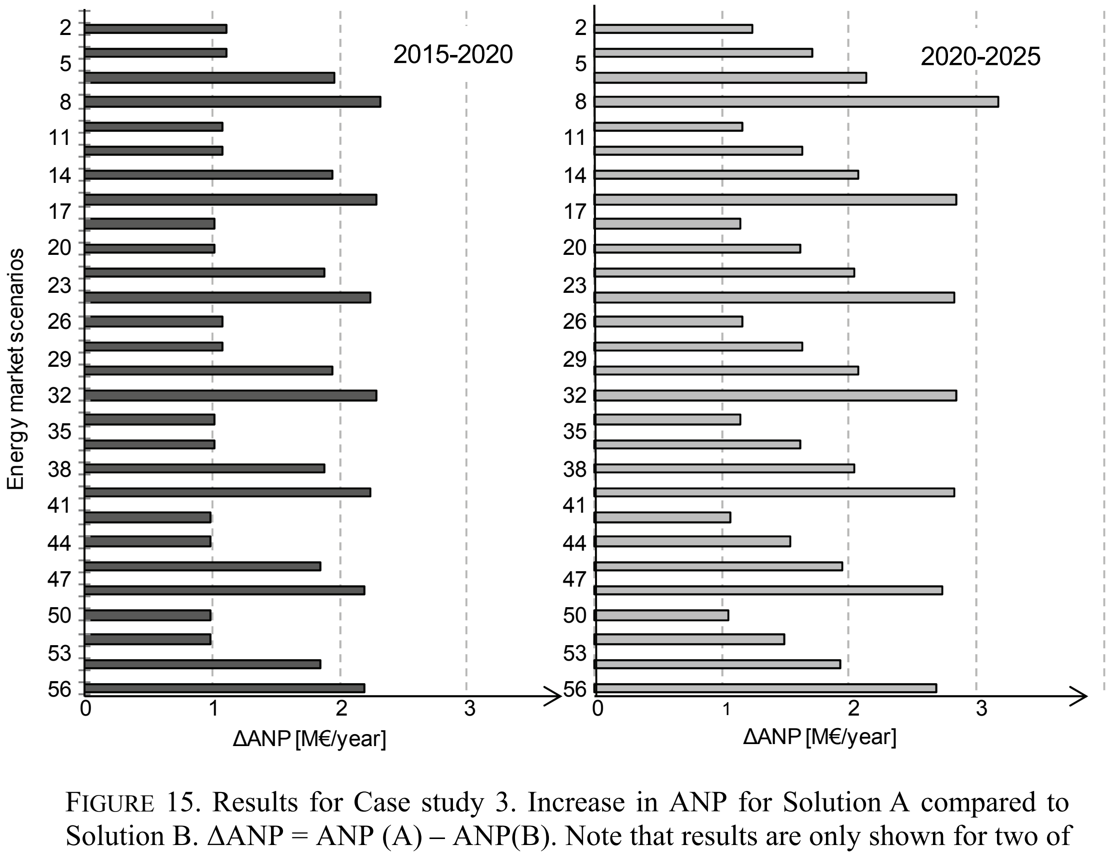

FIGURE 15. Results for Case study 3. Increase in ANP for Solution A compared to Solution B. ΔANP = ANP (A) – ANP(B). Note that results are only shown for two of the six time periods studied.

In Figure 15, the scenarios in which lignin never receives a higher added value are denoted by odd numbers. For these odd-numbered scenarios, the difference in ANP between the solutions achieved for (A) and (B) is zero since district heating deliveries will be optimal regardless of the long-term contract assumption. The scenarios representing a future possibility of receiving a higher added value for lignin are denoted by even numbers. As can be seen, the increase in ANP, when there is no long-term contract (that is, the cost of the lock-in situation), varies from about one million up to over three million euros per year in 2020–2025 in those scenarios. This is a significant amount compared to the actual ANP, which varies between €5.2 million and €11.5 million per year for those scenarios in that time period. These results are further discussed in Section 8.2.

7.2.5 Case study 4 – Including uncertainty in technology development

As proposed in Paper V, the uncertainty in the investment cost development of new technologies is proposed to be studied using scenario analysis. In that case, optimization only determines the optimal solution (under uncertain energy market conditions) for one cost development scenario at a time. Therefore, the comparison of different solutions over all cost development scenarios becomes a requirement for determining the best overall solution. The proposed approach to uncertain investment cost developments was used in Case study 4 both in Paper V (without considering lead times) and in Paper VI (with lead times).

No lead times considered (Paper V)

In Paper V, the proposed approach to modelling investment cost uncertainty was illustrated using Case study 4 with two examples of future technologies which were studied separately: CO_2 capture and lignin separation. The example of CO_2 capture showed that not all anticipated future technologies affect the optimal decisions about which investments should be made today. However, the example of lignin extraction, which is presented in this section, showed that technologies that can be expected in a near future at a competitive cost are highly important to consider today.

Three alternative investment plans (I1–I3) were identified as optimal for at least one cost development scenario (see Table 7 for scenario definitions) assuming a uniform probability distribution over the energy market scenarios. Two investment alternatives (I4–I5) were added for comparison (see Table 12).

TABLE 12. Investment alternatives analyzed in Case study 4, Paper V.

Investment alternative	Description of the initial investment package (Only distinguishing characteristics are presented)
I1	Cogeneration, no heat pump
I2	Cogeneration, small heat pump
I3	Cogeneration, large heat pump
I4	Electricity production only, no district heating
I5	All investments postponed, hence no investments in 2010

Figure 16 illustrates the expected value of these five investment alternatives. The main decision is shown to concern whether investment should be made in a large heat pump today or not. The optimal decision will depend on the probability assumed for the ‘Never’ scenario in which lignin extraction is never supposed to be available on a commercial scale. The decision to invest in a large heat pump is connected to the risk of future lock-in effects (see further Section 8.2). As can be seen, one of the worst alternatives in all the scenarios is the one where no investment is made today. This result implies that it is worth making investments in electricity production today – either with or without cogeneration of district heating – while waiting to see whether the lignin separation technology will be an option in the future.

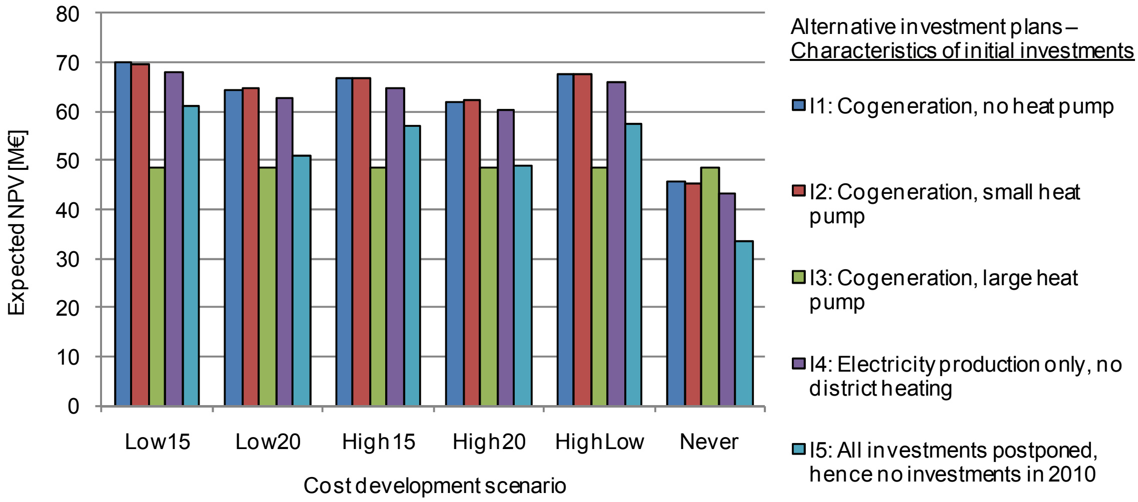

FIGURE 16. Results for Case study 4. Expected NPV of five investment alternatives for different realizations of cost development scenarios (see Table 7).

It should be noted that Figure 16 only illustrates differences in the initial investments of the investment plans. Depending on the realization of energy market conditions and of the cost development of lignin extraction, there will also be differences in future investments. The analysis of the complete investment plan which was performed in Paper V showed that investment in lignin extraction is included in the optimal investment plan for all energy market scenarios in all cost development scenarios except the 'Never' scenario in which the technology never becomes commercialized. Furthermore, a sensitivity analysis of the higher cost levels included in the cost development scenarios showed that the cost level of the lignin extraction technology was of limited importance. It could also be seen that the development of the price of lignin had a larger influence on the timing of the investment in lignin extraction than the timing of market introduction of the technology in the cost development scenarios.

For each cost development scenario, the investment decisions are optimized under uncertainty in the energy market conditions. Figure 17 shows the results for cost development scenario 'High15'. The figure illustrates the difference in NPV between the three solutions I1–I3 defined in Table 12, where I1, which is optimal under uncertainty, has been chosen as the reference solution. It can be seen that I1 and I2 are more robust to variations in energy market conditions than I3, which for some scenarios yields a significantly poorer result. The choice between I1 and I2 depends on which scenarios are believed to be the most probable.

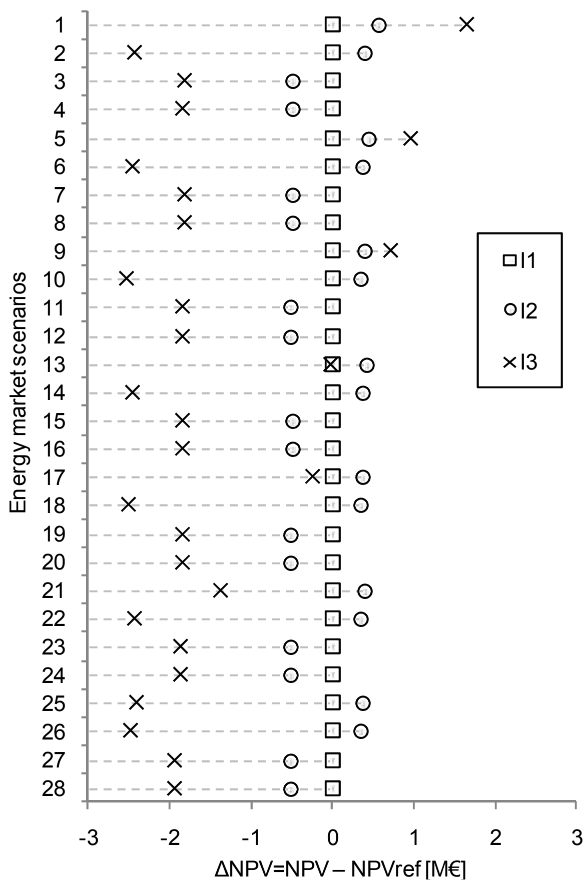

FIGURE 17. Results for Case study 4 and cost development scenario ‘High15’. ΔNPV is the difference between the NPV of the marked investment alternative and the NPV of the reference investment (I1).

Considering lead times (Paper VI)

Case study 4 was also used for the study of lead time effects in Paper VI. To find planning alternatives, the model was solved for one cost development scenario at a time to identify the optimal investment in 2015. A few other planning alternatives were also added based on experience from working with the model and the mill. The investigated planning alternatives are presented in Table 13.

TABLE 13. Alternative plans for investments to be implemented in 2015. Investment planning performed in 2010. (Case study 4, Paper VI)

Investments planned in 2015	Optimal in cost development scenario
Lignin and heat pump	Low15, High15 & HighLow
Cogeneration only	Low20 & High20
Cogeneration and heat pump	Never
Condensing turbine and heat pump	Added for comparison
No investment	Added for comparison

If there are no lead times for planning the decision should be postponed until 2015 to invest in the best alternative for the scenario that is realized. Considering the lead time, the investment planning needs to start today (2010), before knowing the situation in 2015.

Figure 18 shows the planning matrix used to structure the optimization runs. It indicates how to change the model by adding constraints to assess the value of the different investment alternatives. The Xs in the matrix indicate that an investment is possible, though not required. This means that for the first planning alternative, there is a possibility in 2015 to invest in a lignin extraction plant and/or in a heat pump. It is, however, always possible to withdraw from one or both of these investment options. The model is run for each investment alternative and solved for the value of the investment plan for all different cost development scenarios.

		Possible to implement 2015				
		Lignin	Heat pump	District heating from 145 and 100°C heat	Turbine (145-100°C)	Turbine (100-35°C)
Plan 2010	Lignin and heat pump	X	X			
	Cogeneration only			X	X	
	Cogeneration and heat pump		X	X	X	
	Condensing turbine and heat pump		X		X	X
	No investment					

FIGURE 18. Matrix of possible technology implementations depending on what has been planned for.

The expected NPV for the alternatives in the different cost development scenarios is shown in Figure 19.

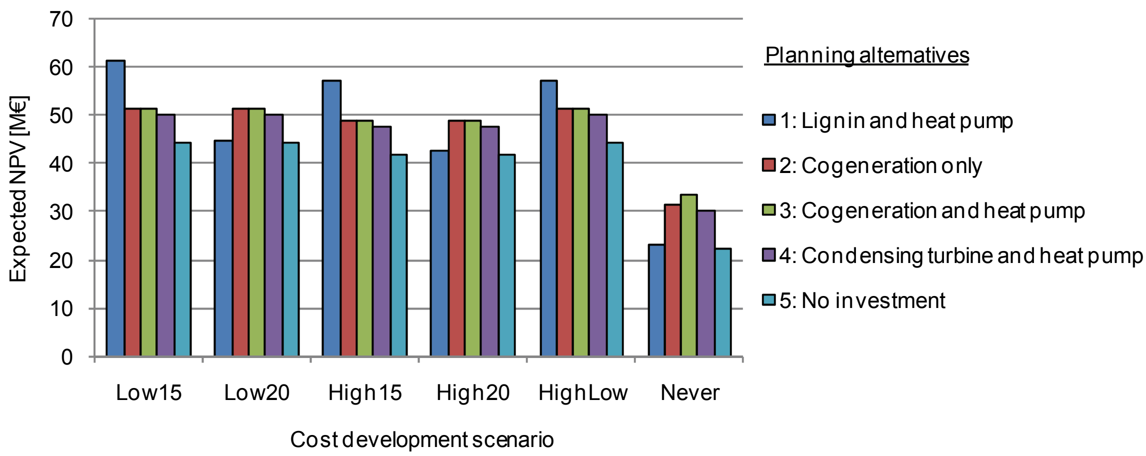

FIGURE 19. Expected NPV for different planned investments in 2015.

The results show that the timing of lignin extraction commercialization is more important than the investment cost level. Depending on whether the lignin separation technology becomes available in 2015 or 2020 (or never), lignin extraction could either be by far the best or by far the worst alternative (except planning for nothing). This is explained by the large potential associated with this technology if it becomes a reality and which disappears if the technology does not become available for the pulp mill. The good runner-up is instead cogeneration, which is either the best or the second best alternative in all scenarios. As anticipated, the 'nothing' alternative is the worst one in all scenarios.

Because of the assumed lead time, the investment plan needs to be decided on today without knowing which scenario will be realized. This lack of flexibility obviously has a cost. The results show that if lignin extraction is not planned for, but cogeneration instead, the loss is 19% in expected NPV in Scenario 'Low15' (17% in 'High15' and 12% in 'HighLow'). On the other hand, if the plan is for lignin extraction and a heat pump but the lignin separation technology does not become a possibility, the loss is 15% in Scenario 'Low20', 15% in Scenario 'High20' and even 46% in the 'Never' scenario.

8 Analysis of main findings and discussion

In this chapter, common findings from using the proposed methodology in the case studies are discussed. The discussion covers aspects related to both the results of the case studies and the proposed methodology.

8.1 Common features of the optimal investment plan

Although the purpose of the case studies in this thesis was to illustrate different methodological aspects, it was also possible to see some common features of the optimal solutions. Many of these have also been seen in unpublished results obtained for working versions of the case study models which indicates some degree of generality. These common features will be described here.

8.1.1 Investments for energy savings are typically favourable

All of the case studies show a clear profitability of investments for energy savings. Regardless of which technologies are included in an investment package, energy savings are typically maximized (with a few exceptions). This is of course explained by the low cost of the energy savings compared to the cost of turbines, lignin extraction plants and other energy-conversion technologies, while at the same time, revenues from the other technologies are obtained due to the synergy effects of combining them with energy savings. However, the input data for energy saving opportunities has been taken from other studies for which only the most cost-effective measures have been reported. This implies that the energy savings included in the model have been pre-optimized based on assumptions that might not be valid in our methodological approach. A too extensive pre-optimization should therefore be avoided although some kind of screening of investment options might be necessary. In Section 8.5 the data used in the model is further discussed.

8.1.2 A low-pressure turbine is a robust investment option today

The optimal initial investment under uncertainty has, for all case studies, included a condensing turbine or a low-pressure turbine with combined district heating production. It thus seems that investment in electricity generation is robust even for the poor efficiency of a condensing turbine.

Even in Case study 1, when lignin extraction is chosen in order to avoid the recovery boiler upgrade, lignin extraction is held at a minimum to enable maximum electricity generation. When the lead times for Case study 4 were considered, investments today were not assumed possible, and although the planning alternative for lignin extraction has great potential, the planning alternative including a low-pressure turbine seems more robust. When lead times were *not* considered in Case study 4, it could be seen that investment in a low-pressure turbine was optimal today even when it would be replaced by lignin extraction within five years. That result could, however, be explained by the favourable conditions for district heating production in combination with the turbine option.

Electricity generation is obviously favoured by the system of green electricity certificates in place in Sweden, where all the mills in the case studies, except Case study 2, were assumed to be located. It can also be seen that for Case study 2, the benefit of electricity generation is less pronounced.

It is very difficult – and risky – to generalize the results from the case studies and claim that electricity production will always be profitable since the results are heavily dependent on economic assumptions, mill-specific conditions and alternative investment opportunities. However, the results are interesting in another perspective. They show that, even if there are technologies that are promising for future implementation, this is not necessarily a reason to postpone all investments. There might very well be investment options today (such as the condensing turbine in our examples) that are profitable enough within a short term to give a return on investment before the alternative technologies become interesting.

8.1.3 Lignin extraction might be an interesting future investment, but will probably not affect the optimal initial investment

Lignin extraction has been included in all of the case studies, although with different assumptions about the value of lignin. The overall impression from all case studies is that lignin extraction might be an interesting investment option in the future. However, it is optimal as early as today only in Case study 1 where it provides a way to avoid the very capital-extensive investment in the recovery boiler.

However, the results indicate that there is often no reason to avoid investments in traditional technologies today (e.g. electricity production or district heating) as long as lock-in situations that would make future implementation of lignin extraction drastically more expensive are avoided. These results are partly explained by the assumptions about green electricity certificates and district heating conditions, and partly by the low discount rates used because the investments are viewed as strategic investments.

8.1.4 Few alternatives for the initial investment

Mathematical programming is a good approach for systematically identifying the optimal solution from a large number of feasible alternatives. However, in each of the case studies, only a few distinctly different alternatives for the initial investments were identified. This could indicate that the potential of the optimization methodology is not fully utilized. However, the addition of more alternatives to the model increases the demand for process and technology data that is typically not easily available (see Section 8.5 for further discussion).

8.1.5 District heating conditions have a large influence on the results

Since most of the studied mills are model mills, assumptions have been made about the conditions for district heating deliveries. These assumptions have been shown to significantly influence the optimal investments, since district heating many times competes directly with technologies for internal use of excess heat. These results indicate that when the methodology is applied to a real mill, the conditions regarding district heating will be especially important to model properly (see Section 8.6 for further discussion).

8.1.6 The modelling of the bark boiler is important for correct valuation of flexibility

For some of the studied mills it was possible to vary the load in the bark boiler. Optimized operation of the bark boiler has been shown to be of importance for flexibility, both in the investment planning, and in the operation of the mill. Since the value of bark is rather low, the value of this flexibility must be considered to capture the advantages of a reduced load in the bark boiler. This was seen in Case study 2 and in work on Case study 3. It is therefore important to model the bark boiler properties correctly with regard to minimum and maximum load limitations and seasonal variations (see also Section 8.7).

8.2 Lock-in effects

The methodology proposed in this thesis has shown to be especially valuable for the analysis of lock-in effects. Lock-in effects were first studied in Paper IV and later in Paper VII. A lock-in situation typically arises because earlier decisions were made without enough consideration to the flexibility required to meet future changes[9]. By including future changes and future investment opportunities in the investment optimization model, the investment leading up to a lock-in situation will not be identified as optimal. In this section the case studies are discussed with regard to the identified lock-in effects and how the cost of such lock-in effects can be estimated.

Case study 1 provided a clear example of how consideration to future changes in external conditions can help in avoiding lock-in situations. By considering the future possibility of increasing lignin prices, the risk of a lock-in effect connected to the capital-intensive RBU can be identified and quantified. In four of the six energy market scenarios modelled, the cost of RBU lock-in varied between 12–38 million euros, corresponding to a 12%–31% reduction in NPV (see also Figure 12).

In *Case study 2*, the optimal solution in some scenarios was to invest in a large turbine, while in others it was to invest in a lignin extraction plant. However, the optimal solution under uncertainty was to invest in a small turbine, and reduce the load on the bark boiler (see also Figure 14). This way, possible lock-in to a lignin extraction plant is avoided, and by the choice of a small turbine, the effect of possible turbine lock-in is also reduced. This

[9] Here, we do not consider behavioural lock-in effects due to irrational decisions assigning a value to sunk costs.

is a good example of the value of flexibility and how it can be utilized to avoid lock-in situations. The option to reduce the bark boiler load is flexible in the sense that there is no cost associated with the change in the operation of the boiler. Even though it is always preferable to either export electricity or lignin over bark, the possibility of exporting bark provides a way to benefit from the energy savings while waiting to see in which direction the energy market will develop, and whether electricity or lignin will be the most profitable.

Case study 3 is another clear example of how failing to consider possible future changes can lead to lock-in situations. When the future possibilities of high lignin prices are not considered, a district heating cooperation is the optimal strategy for the mill. However, when considering possible future change (increased lignin value), it could be seen that district heating deliveries might only be interesting for a short time period. The risk of lock-in associated with a long-term district heating contract can then be identified. As shown in Section 7.2.4, the cost of district heating lock-in is between one and three million euros per year in 2020–2025 if higher lignin prices become a reality. This corresponds to 19%–28% of the ANP obtained when avoiding the lock-in situation.

The lock-in effects are also clear in *Case study 4*. A large heat pump would bring substantial earnings during some years in the near future. On the other hand, it would result in significant lock-in effects if the cost of the lignin extraction plant decreases in the future. By investing in a large heat pump, the mill commits to extensive district heating deliveries and future lignin separation is impossible. Compared to not investing in a heat pump, this would result in a drop in NPV of up to 30.6% for the future cost development scenarios where the lignin extraction technology becomes available (see also Figure 16). This result indicates the cost of the lock-in effect in case of lignin extraction commercialization.

As illustrated, the effect of lock-in situations can be evaluated by using the methodology described in this thesis.

8.3 The value of future investment opportunities

Paper VII discusses the importance of modelling how external conditions develop over time and how a mill can react to changes in its surroundings by making new investments. By including the value of future investment opportunities this way, the model will capture the advantage of flexibility in an investment plan. The modelling of future changes in external conditions and the opportunities for later investments enables the study of lock-in effects as discussed in Section 8.2.

The results from Case study 2 will be used to illustrate the significance of the value of future investment opportunities. In Figure 20, the value of the investment alternatives presented in Table 11 is divided into the value of the investments made today and the value of future investment options. Investment alternative I4 is optimal under uncertainty assuming a uniform probability distribution.

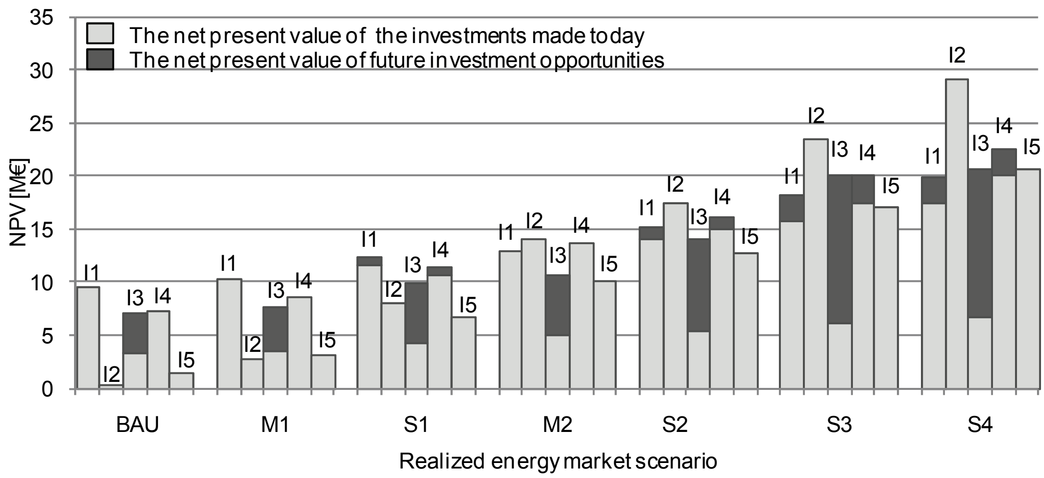

FIGURE 20. Results for Case study 2. NPV of the five investment alternatives (I1-I5) for different realizations of energy market scenarios.

One of the investment alternatives I1 and I2 is optimal in each scenario. However, investment alternative I3, which more or less is a wait-and-see solution, is actually a good competitor although the value of the investment made today is quite low. By including the value of the future investment opportunities I3 becomes a robust alternative. In this case study, however, investment alternative I4 is even better. It is actually the second best solution in each scenario and is the optimal solution under uncertainty assuming a uniform probability distribution.

As was also shown in Paper VII, this modelling of future changes and investment opportunities is one of the major advantages of the proposed methodology.

8.4 Robustness of the solutions

The robustness of the solution may refer to the robustness either with regard to variations in surrounding conditions (i.e., the scenarios) or more specifically with regard to the probability of the scenarios. General robustness is discussed in Section 8.4.1. Robustness with regard to variations in the assumed probability distribution is discussed in Section 8.4.2

8.4.1 Robustness of solutions over varying scenarios

Robustness can be defined in many ways. Here, a solution is said to be robust if in each scenario it is one of the best solutions, or if its value is close to the optimal value. This definition of robustness is clearly subjective and used here in a relative sense. For example, in Case study 1 (see Section 7.2.2), the solution I2 is more robust than I1 since the value of I2 is always close to the optimal value in each scenario.

A solution can be robust even if its value varies significantly for different realizations of the uncertain parameters. These variations depend on external conditions that cannot be affected by the mill. When comparing the robustness of different solutions, the differences between solution values within a scenario are therefore those which are essential to consider.

The comparison of different solutions, using bar charts like in Figure 12 and Figure 14, does not require a methodology for optimization under uncertainty. However, the stochastic programming approach is required to ensure that the optimal investment plan under uncertainty is identified to be included as one of the compared alternatives. A solution that is robust, but never optimal in any single scenario would not be identified by only using scenario analysis. One such solution is the solution alternative I4 in Case study 2, which is the second best alternative in each scenario (see Figure 14).

While the stochastic programming approach guarantees that such a robust solution is identified if it is optimal, the optimal solution under uncertainty is not necessarily a robust solution. For a given probability distribution, the stochastic programming approach determines the optimal solution as the solution that possesses the best expected value. A solution may yield the maximum expected value by being very good in some scenarios and quite bad in others. In Case study 2, again, the solution I2 would be optimal if the probabilities of Scenarios S2–S4 were significantly higher than the probabilities of the other scenarios (see Figure 14). Nevertheless, robust solutions will typically be favourable under uncertainty – as identified in the stochastic programming approach – since they do not reduce the objective value by poor performance in some scenarios.

Furthermore, robustness can always be evaluated by comparing different solutions, including the optimal solution identified using stochastic programming. The decision might then be a trade-off between robustness and expected value. If robustness is of particular importance in some application, there are possibilities to include risk measures explicitly in the optimization model, either in the objective function or in the constraints (see also Section 10.1).

8.4.2 Sensitivity to variations in the probability assumption

Since the probabilities of the scenarios used in the stochastic programming model are assumed to be unknown for this application, it is important that the robustness of the solution can be evaluated with regard to the probability distribution.

In Paper II, a straightforward sensitivity analysis of the probability distribution was illustrated. There, the optimization model was simply solved for five different probability distributions. For Case study 1, all five probability distributions yielded the same optimal solution, indicating in that case that the optimal solution was not sensitive to moderate variations around the assumed probability distribution.

Another approach was proposed in Paper III (Case study 2). In this approach, the probabilities were systematically varied to find out how much the distribution could deviate from the original assumption without altering the optimal solution. Starting from the original probability distribution assumed, the probability of one scenario was increased while the probabilities of the other scenarios were uniformly decreased until there was a shift in the optimal solution – a breakpoint. Also if this analysis shows that the solution is not robust, that is, if the breakpoint is close to the original probability, the approach improves the understanding of how uncertainties affect the optimal solution. This is done by providing limits for when the obtained solution remains optimal. The decision-makers can then judge whether they believe that the probabilities will lie within these limits or not, and do not have to specify an exact probability distribution.

In Case study 2, the original probability distribution was assumed to be uniform, that is, with equal probabilities for all seven scenarios (~14.3%). Since the optimal solution under uncertainty, in this case study, was not identified as the optimal solution for any single scenario, there is at least one breakpoint – between 14.3% and 100% probability – for each scenario. Table 14 shows the identified breakpoint probabilities.

TABLE 14. Sensitivity analysis of the probability distribution in Case study 2. All breakpoint probabilities between 14.3% and 100% for which there is a change in the optimal solution.

Breakpoint probability (%)						
BAU	M1	S1	M2	S2	S3	S4
22.8	25.1	33.6	19.8	42.1	25.3	21.0
			66.9[a]			

[a] The first breakpoint with a change in the initial investment.

The probability for scenario S2 can increase to 42.1% before the solution changes. The breakpoint probability for scenario S1 is also rather high at 33.6%. Breakpoint probabilities at this level might be considered quite robust – that is, quite far from the assumed probability of 14.3% – based on whether or not the decision-maker believes in the uniform probability distribution. The breakpoint probability for scenario M2 is, however, rather low (19.8%), but the initial investment in the solution is not changed until the probability increases to 66.9%, meaning that the initial investment seems to be robust with respect to the probability of the M2 scenario. The breakpoint probabilities of scenarios BAU, M1, S3, and S4 are, however, lower. The assumptions made about the probabilities for these scenarios are therefore quite important.

In Paper III, the probability distribution was varied by increasing the probability of one scenario, while decreasing the probabilities of the other scenarios uniformly. It should be noted that the probability distribution may also be varied in several other ways.

8.5 Data availability

In Section 8.3 and Paper VII the importance of modelling future changes and investment opportunities in order to value flexibility correctly was discussed. In Section 8.4, the connection between the stochastic programming approach and the valuation of robustness was discussed. However, it is only possible to benefit from these features of the modelling approach if robust investment options that provide flexibility are actually included in the model. Additional data might therefore be required compared to a traditional investment evaluation method where flexibility and robustness are not given any value. For example, data is desired for the added investment cost required to achieve operational flexibility, and for the investment cost of step-wise implementation of investments through future extensions or modifications to existing equipment.

The availability of this type of data is limited since investment costs and process data are normally given for fixed equipment sizes or certain process configurations. The process integration and biorefinery measures are therefore modelled as discrete packaged alternatives for which cost and process data are available. If a ‘package’ is combined with other measures or if changes are made over time, relevant data does often not exist.

Consequently, in reality, there are often more possibilities for different degrees of heat integration and other energy-efficiency measures than what has been modelled in our case studies. This is because input data is based on results from previous studies for which typically only one or a few packages of energy-saving measures have been presented. In previous studies, assumptions have often been made about some measures not being interesting because of lower cost-effectiveness or because they are not interesting in combination with the technologies investigated in that particular study. These kinds of assumptions imply a pre-optimization that may not be relevant in our model where other technologies and another time perspectives are considered. This pre-optimization limits the possibilities of combining different parts of these packages or of step-wise implementation. Furthermore, the cost of the energy savings has rarely been a limiting factor. Instead the optimal solution often implies maximization of energy savings. This implies that further, more costly energy savings than what have been modelled could also be interesting (see also Section 8.1.1).

To overcome the challenge of obtaining relevant data, it is important to have a good cooperation with manufacturers and technology developers in developing a mutual understanding of the importance of establishing data for flexible and robust technology investments. Furthermore, the pinch analysis performed to identify process integration measures to include in the model should, preferably, be conducted with knowledge about the proposed optimization approach – thereby avoiding pre-optimization pertaining to the extent of the heat savings.

No model is better than the quality of its input data. If the problem with data availability remains, and the investment problem in future applications tends to be a choice between a few discrete investment alternatives, a real-options approach (e.g., using dynamic programming) might be an interesting alternative to the approach proposed in this thesis.

8.6 Conditions for district heating deliveries

As discussed in Section 8.1.4, the opportunities for district heating deliveries will have a major influence on the optimal investment strategy for the mill. Since the mills used in the case studies do not represent any real mills, it has been possible to make free assumptions about the conditions for district heating. Since district heating deliveries compete directly with technologies using excess heat internally at the mill, the investment plan is often completely changed if the conditions for district heating are varied.

The potential for and profitability of district heating deliveries are dependent on a number of factors such as the heat-load duration curve of the district heating demand, the existing heat production in the district heating system and the price-setting criteria for the delivered heat. Furthermore, in a strategic perspective, these factors cannot be assumed to be constant. There might be opportunities for expansion of the district heating network, thereby changing the heat-load duration curve; the district heating production capacity might be increased; production capacity might be replaced by new technologies; and the contract between the mill and the district heating company might be re-negotiated. The connection of the mill to a district heating system will also have a significant effect on the degree of variations in mill process parameters (see Section 8.7).

Since the assumptions made regarding these factors have been shown to significantly influence the optimal investment plan of the mill, it is important to model them properly when the methodology is applied to a real mill. This will, undoubtedly, be a challenge since the modelling will also involve the future plans of the district heating company. To complicate things even more, these future plans might very well be dependent on the mill's decisions; for example the connection of more customers to the district heating grid might depend on the potential for the mill to provide excess heat to the grid.

To summarize, it is important to model district heating conditions correctly, while at the same time it might be difficult. However, it is always possible to perform a sensitivity analysis for the parameters that are uncertain in order to improve the understanding of the investment planning problem. What is most important therefore is to be aware of the significance of the district heating assumptions.

8.7 Seasonal variations

Because our focus has been on long-term changes and uncertainty, the heat balances of the case study mills have been modelled as annual averages. The case studies have shown, however, that the assumptions made to simplify seasonal variations to linear functions of annual averages can significantly influence the results. Since this has not previously been discussed in any of the thesis papers, the effects of the assumptions connected to seasonal variations are explained in this section.

Pulp mills connected to district heating systems are especially affected by large variations in heat demand over the day and over the year. Also the hot and warm water system of a pulp mill process is affected by seasonal variations due to variations in ambient conditions. As a result, the potential for steam savings will also vary [78, 79]. These types of variations originating from the secondary heat system are, however, likely to be reduced by more extensive heat integration. Also in a long-term perspective, as assumed throughout this thesis work, the heat demand variations of a shorter time scale can be important to consider. The reason is that technologies and processes are flexible to variations to a varying degree and this flexibility can be an advantage.

In a pulp mill, seasonal variations in steam demand are typically controlled by varying the steam production in the bark boiler. Figure 21 illustrates a typical heat-load duration curve for the steam demand of a market pulp mill that is connected to a district heating network. The heat load duration curve is a simplified function representing approximately the average steam demand of the mill studied in [79] with the relation between maximum and minimum district heating demand being approximately the same as for the medium district heating system studied in [27][10].

[10] The few days with top-load demand are, however, assumed to be covered by alternative heat supply.

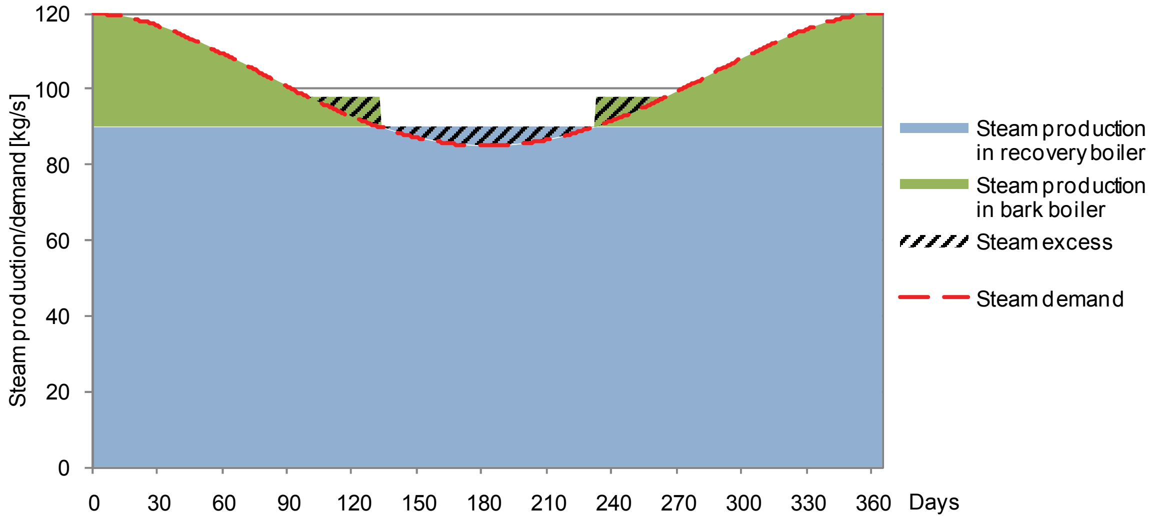

FIGURE 21. Steam production in the bark boiler and the recovery boiler of a market pulp mill. Combined steam demand of the pulp mill process and a connected district heating system.

Figure 21 also shows how steam demand is covered by the constant steam production in the recovery boiler and by the varying steam production in the bark boiler. Because of the minimum load limitation on the bark boiler and the constant steam production in the recovery boiler, there will be an excess of steam during parts of the year. It is clear from the figure that there is a lack in the flexibility of the bark boiler to control the steam balance of the mill. However, in the current situation, the amount of steam that is vented to the atmosphere is still fairly small.

Figure 22, on the other hand, shows the situation after a retrofit of the mill to save steam. Here, the amount of excess steam becomes significant and the limited flexibility of controlling the steam balance with the bark boiler operation becomes obvious.

A technology that could yield flexibility in this kind of situation is lignin extraction. The extraction of lignin would be a way to control steam production also in the recovery boiler. This is illustrated in Figure 23, where the operation for a given steam demand was determined by first minimizing steam excess, and then maximizing lignin extraction. The capacity of the lignin extraction plant was assumed to correspond to the steam savings. The flexibility in meeting variations in steam demand would be an advantage for lignin extraction compared to bark savings which could not be captured in a straightforward way in a linear model that only uses annual averages.

In our stochastic programming model, the outputs (e.g. the bark savings or the lignin extraction) are determined by a number of linear relations such as energy balances and capacity constraints. If constant conditions are assumed over the year, these constraints are usually straightforward to formulate. If the bark boiler, for example, is constantly run at the same load during the whole year, this load is also the maximum bark savings possible. However, when large variations are considered, the constraints are more difficult to determine. The potential for a reduction or increase in bark as an annual average will, for example, depend on the other technologies implemented. The formulation of such relations makes it difficult to keep the model linear.

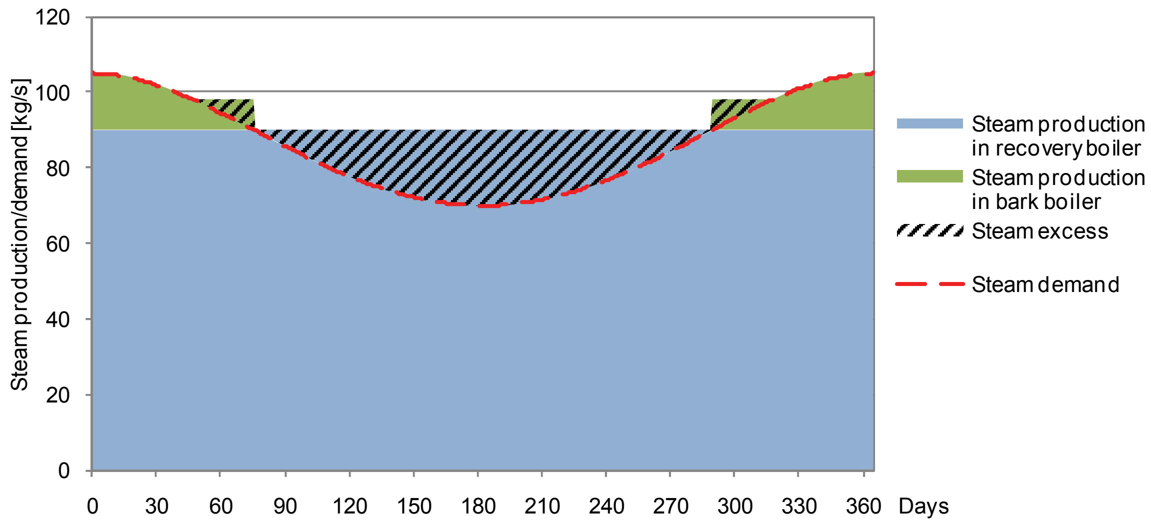

FIGURE 22. Reduced steam demand of the mill and district heating system after steam savings. Steam production adjusted in the bark boiler only.

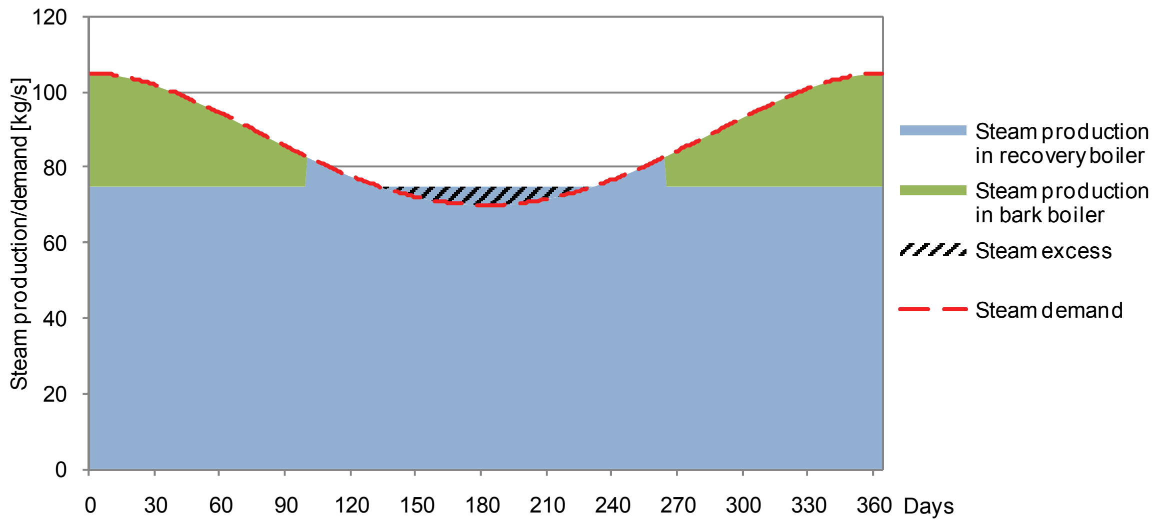

FIGURE 23. Reduced steam demand of the mill and district heating system after steam savings. Steam production adjusted in both the bark boiler and the recovery boiler. First priority: Minimize steam excess. Second priority: Maximize lignin extraction (= minimize steam production in recovery boiler).

A number of different assumptions can be made to simplify the varying conditions to annual averages. It is, however, usually impossible to find one simplification that comes close to correct results under all conditions. Figure 24 illustrates how three different assumptions for the linear constraints of the bark savings compare with the correct solution based on the load-duration curve. The figure includes four sets of data (A–D) for the total steam saving and the lignin extraction capacity to illustrate that although one assumption might be sufficiently accurate under some conditions (e.g. all assumptions in Case B), it might not be for others.

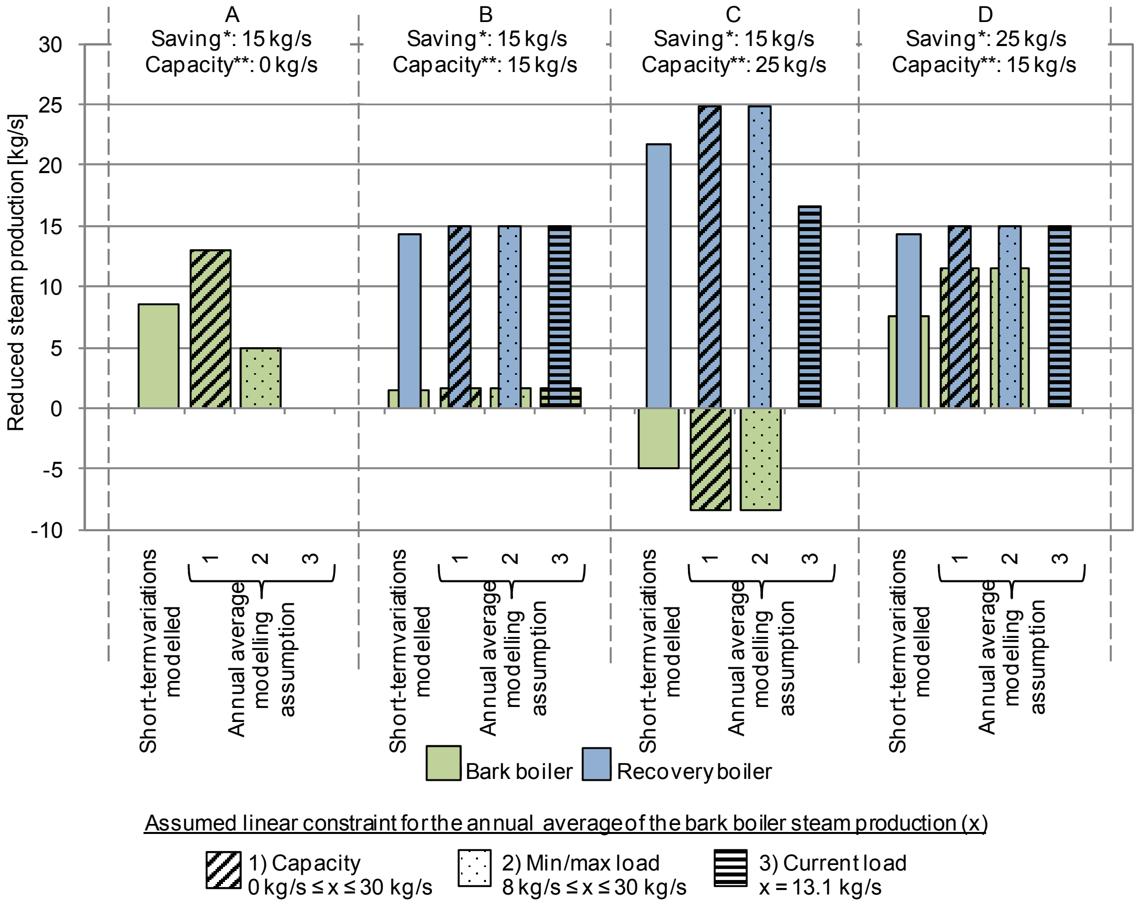

FIGURE 24. Calculated reduction in steam production in the bark boiler and recovery boiler for four different sets of data for the (*) total reduction in demand of high-pressure steam and for the (**) capacity to reduce the steam production in the recovery boiler through lignin extraction. In addition to the solution for which the seasonal variations are modelled explicitly, three solutions are shown in which different linear, annual-average constraints have been used for the bark boiler steam production.

The results for the assumed linear constraints are calculated based on a number of assumptions:

- The steam saving should equal the sum of steam production reduction in the bark boiler and the recovery boiler.
- The annual average of lignin extraction is only constrained by the capacity for lignin extraction.
- Lignin is assumed to have a value sufficiently high in relation to the bark value to give lignin extraction priority over bark savings given a certain lignin extraction capacity. This will sometimes even lead to an increase in the use of bark.

Furthermore, for each calculation the steam saving and the capacity for lignin extraction have been fixed, but it has also been assumed that there is no alternative use for excess steam. These are all variables that should be optimized in the model. Considering that these figures therefore only show a very limited set of potential values for the model variables, a generalized formulation of correct annual averages can only be determined in the optimization model by including the daily heat-load data and refining the model to shorter time steps (see also Section 10.2).

In our studies (see e.g. Case study 1, Paper II) the seasonal variations in the heat demand for district heating have been modelled. However, the connection between variations in district heating and other technologies has not been considered. For example, the possibility to use excess heat for district heating during the winter season and for something else, such as electricity production, during the summer has not been modelled. Instead, constant conditions were assumed for all technologies except district heating, and a constant allocation of excess heat to district heating was assumed over the year.

Finally, variations in energy prices, such as the fluctuations in electricity or carbon prices might also be essential to model if technologies and systems solutions that are flexible in operation with regard to such changes are considered (see e.g. [146]). Such operational flexibility can be important to consider also in a strategic investment analysis (see e.g. [147]). So far, no obvious examples of this issue have been seen in our case studies, and therefore it has not yet been studied in more depth. The problem of modelling these types of variations is, however, closely connected to the modelling of other variations of the same time-scale.

9 Conclusions

This thesis presents a methodology for the optimization of strategic investments in process integration and biorefinery processes in pulp mills under uncertainty. The work with methodology development and the results from a number of case studies has led to some general conclusions and recommendations regarding strategic process integration investment planning:

A model for the strategic optimization of investments in process integration should include how the values of different parameters change over time. Examples of important parameters are the energy market conditions surrounding the mill and the investment costs of emerging technologies. The proposed scenario-based modelling of these parameters captures uncertain changes in the parameter values over time.

It is important to model both current and future investment decisions. While the external conditions change over time, the internal decisions should be responses to these changes. Consequently, there is a need to model investment opportunities at multiple points in time. The proposed modelling of uncertainties and decisions as a scenario tree yields a better understanding of how investments made now affect later investment and operation opportunities in a long-term perspective. The modelling of multiple investment opportunities affects the data requirement of the model. For example, data pertaining to step-wise investments and process improvements is required.

A proper modelling of change is required to capture the value of flexibility in the investment plan. There is a strong connection between possible future change, flexibility and the risk of lock-in effects. The modelling of scenarios that represent a change over time in combination with the modelling of both current and future investment opportunities enables a valuation of the flexibility in the investment plan. A lack of flexibility risks leading to lock-in situations in which future investments which could lead to high revenues are made drastically more expensive. The value of flexibility can be quantified by the calculation of the cost of associated lock-in effects. We have shown that this cost, or equivalently the value of the flexibility, can be significant. However, there is always a trade-off between the value of the flexibility and the investment costs required to obtain it. The methodology proposed in this thesis provides means to optimize this trade-off.

The stochastic programming approach as proposed in this thesis gives a guarantee that a robust solution, which is optimal in expected value, but never in a single scenario, can be identified. When the expected value of the NPV of the investment plan over all scenarios is evaluated, as in the stochastic programming model, the robustness of the investment plan will be favourable. The robustness of an investment plan can also be evaluated by comparing it to alternative solutions. However, the use of the stochastic programming approach is required to ensure that the optimal solution under uncertainty is identified to be included for comparison.

It is important to assess the robustness of the solutions with regard to the assumed probabilities of the uncertain parameters. We have shown examples of how the robustness with regard to the assumed probability distribution can be systematically evaluated. This kind of analysis improves the understanding of how uncertainties affect the optimal solution by providing limits for the probability distribution such that the obtained solution remains optimal.

Even if an emerging technology is not yet commercially available, it can influence the optimal decision about today's investments. Not all anticipated future technologies affect the optimal decisions of today. However, technologies that are expected to become available at a competitive cost in a near future can be highly important to consider in the model. The reason is that the investments made today might affect the possibility to invest in these emerging technologies when they become available. This can lead to lock-in effects in the future, thereby reducing the value of the long-term investment plan.

It is important to consider the long lead times involved in investment planning. Long lead times result in a loss of flexibility since investments plans must be determined long before knowing the future development of energy prices and technology costs. Our investigation of the effect of long lead times shows that significant economic values are associated with this (in-)flexibility. In order to accurately incorporate the value of this flexibility into the optimization of the investment planning process, the lead times must be properly modelled.

Seasonal variations should be explicitly modelled in order to properly value technologies that are flexible in the face of such variations. This is especially important when studying mills that are affected by large variations, for example, from a district heating system. If there are technologies that enable efficient ways of adjusting the operation of the mill's energy system to the varying conditions, then these technologies provide a flexibility that should be considered to be valuable. The value of this flexibility can be captured in the model only if the seasonal variations are properly modelled.

For many mills there are investments in process integration and traditional technology that should be implemented today. Uncertainty regarding future energy market conditions and the development of emerging technology inevitably makes the choice between different traditional and emerging technological options difficult. There is a risk that all investments – and consequently all energy savings and associated emissions reductions – are postponed while waiting for more information on the development of the uncertain parameters. However, our case studies show that there might be technologies today that are sufficiently profitable to give payback before any competing alternative becomes interesting. For example, a low-pressure turbine is often a good investment today even if it competes with lignin extraction which is a promising future technological option. This is because lignin extraction will not become an interesting investment alternative until the price of lignin is higher and the cost of the technology is lower. By then, the low-pressure turbine will already have returned its investment. On the other hand, some of today's investment opportunities will lead to unfavourable lock-in effects if implemented. It is therefore important to evaluate both current and future investment projects in a combined model in order to optimize the investment plan in a long-term perspective. This makes it possible to identify energy savings and technologies that can be cost-effectively implemented today while retaining the opportunity for more far-reaching projects in the future.

10 Future research

This chapter presents some ideas for future work.

10.1 Accounting for risk

The objective function used in the proposed model represents the expected net present value (NPV) of the investments. In this approach, risk is only implicitly accounted for by the choice of the discount rate. In the case studies presented in this thesis, risk has not been deemed to be such an important parameter since all identified investment alternatives have yielded a positive NPV in every scenario. In other applications, there might, however, be a significant risk of negative values in some scenarios even if the expected NPV is positive. The introduction of some kind of penalty function preventing risky decisions in the model may then become important. Different strategies for managing risk and different risk measures in applications related to the energy and biorefinery fields are discussed, for example, in [129, 148–150].

The introduction of a risk function into the model is not entirely straightforward; it requires a clear definition of risk. Work would therefore be needed to investigate what the proper definition of risk would be in this specific context. Examples of considerably different risk functions are the minimization of the variance of the NPV, the minimization of the probability of receiving a NPV below a certain level, or constraints enforcing a positive NPV in all scenarios. The risk function can also be introduced in the model in different ways, for example as additional constraints or as a second objective.

The inclusion of risk should, preferably, not drastically increase the computation time needed to solve the model. In practice, this typically requires that the linearity of the model is retained. Including risk without an increased computational complexity could, for example, be accomplished by adding a risk function such as the conditional value at risk to the expected value in the objective function (see e.g. [151]).

10.2 Refining the model time steps

Considering the importance of change and the timing of investments, it would be preferable to decrease the time steps between investment decisions from the currently used five years. This may increase the value of waiting because revenues would not be lost over so many years. The length of the time steps will be increasingly important when approaching the time of a drastic change such as the market introduction of a new technology or a large increase in energy prices.

If the time steps of the investment decision model are shortened, the time steps of the energy market scenario model should be shortened accordingly. This will lead to more stages in the model, by which follows greater complexity since each stage typically involves the branching of the scenario tree. This, in turn, will lead to an increase in the computation time needed to solve the model. In order to enable shortened time steps while limiting the increase in the number of stages in the model, it may be motivated to use a differentiated time scale with shorter intervals close to expected external changes and longer intervals, for example, in the end of the analyzed time span. There is also an opportunity to counteract the increase in computation time to some extent by improved solution algorithms. This requires further research to improve the mathematical model formulation and the algorithms used to solve the resulting model (see Section 10.4).

As discussed in Section 8.7, seasonal variations can also be important to include in the model, this would require the use of time steps of significantly less than one year for the operating decisions.

10.3 Improving the energy market scenario model

A few aspects of the energy market scenario model would benefit from further development. First of all, more parameters may be considered uncertain, for example, the price of green electricity certificates, the price of green transportation fuel certificates and the availability of CO_2 capture and storage for marginal electricity production technologies.

Work is also needed if the length of the time steps of the model is reduced from the current five years. More short-term variations such as those due to weather conditions or market fluctuations will then have a greater influence. Consequently, input data for the construction of scenarios cannot solely be based on the reference material that have been used so far.

Future work should also focus on the modelling of scenarios that represent a development over time in a plausible way. The latest version of the scenario tool includes the possibility to construct scenarios for different years [22]. The conditions for one year are, however, calculated without considering the prices and marginal technologies for previous years and without considering the transition from one set of conditions to another. Therefore, care must be taken so that the path of change from today to future conditions is plausible. This would involve modelling the transformation from one marginal electricity production technology to another.

10.4 Improving solution performance

Refinement of the time steps of the model and improvement of the energy market scenarios and technological data will result in more realistic mathematical models. These might also result in a clearer advantage of using the MSP approach over the SA approach.

However, there is the clear risk that this could lead to intractable computation times. Future development may therefore be needed to improve computational performance. Possible approaches to this problem could include the mathematical decomposition of the optimization models to enable the development and use of improved solution algorithms (see e.g. [152]), and heuristic algorithms for the identification of close-to-optimal starting solutions.

Decomposition techniques has been used in applications similar to that of this thesis, but with the design variables representing investment decisions that occur only as first-stage decisions in the model [39]. With multiple investment opportunities (design stages), as in the model proposed in this thesis, the model structure will not be as straightforward to exploit for advantageous decomposition. The approach should, however, yet be possible.

Since a large share of the computational effort is often used to verify that optimality is reached, there is also a potential for reducing computation times by allowing the solver to stop prematurely. This means that the solver would return a solution that has not been proven optimal, but for which the objective value has been shown to be within a small percentage of optimality.

10.5 Modelling the cost associated with long lead times

The modelling of lead times as presented in this thesis provides a good starting point for an investment planning methodology in which the long lead times that are often involved in these kinds of decisions are considered. However, future work could improve the methodology through modelling the costs associated with evaluation, planning and detailed analyzes of different investments and their implementation. It should also be possible to differentiate these costs and the length of the planning lead time between different kinds of investment alternatives. Long lead times should also be modelled for later points in time. Currently, they have only been considered for the initial investments.

10.6 Modelling uncertainty in operating reliability

The methodology should be developed to enable the study of other kinds of uncertainties than those included so far. In the Swedish pulp and paper industry, technical risks such as the risk of production disruptions and costs related to these risks have been assessed to be the greatest barrier to investments in energy efficiency [153]. The technical risks originate, in many cases, from the lack of experience of the operation of new technology equipment and system configurations, which leads to uncertainties attributable to operating reliability. Operating reliability would therefore be an interesting parameter to include in future work.

Uncertainty in the operating reliability of a new technology should be correlated with the uncertainty in the investment cost, since both depend on the development of the technology. This implies that operating reliability is best incorporated into the scenarios that have already been developed for uncertain investment cost developments.

10.7 Accounting for emissions reductions

The model can, with minor adjustments, be used to study the trade-off between the NPV and the CO_2 emissions reductions for the investments. The resulting optimization naturally becomes multiobjective (see e.g. [154]). The work to include environmental concerns in the methodology proposed in this thesis has been initiated by the formulation of a two-objective optimization model, which is solved by reformulating the objective on CO_2 emissions as a constraint [132]. Further work is, however, required for the development of the methodology.

Nomenclature

C_0	Initial investment cost
$C_{t,s}$	Net cash flow in year *t* for scenario *s*
$\ell(n)$	Level of node *n* in the scenario tree
n	A node in the scenario tree
$p(n)$	Parent node of node *n* in the scenario tree
p_s	Probability for scenario *s* to occur
r	Discount rate
s	Scenario index
S	Set of all scenarios *s*
t	Time index
T	Lifetime of investments, total time span analyzed
x_m^n	Binary variable indicating if measure *m* is implanted in node *n* or not

Abbreviations

ANP	Annual Net Profit
CCS	CO_2 Capture and Storage
CVaR	Conditional Value at Risk
CHP	Combined Heat and Power
IRR	Internal Rate of Return
LEP	Lignin Extraction Plant
MILP	Mixed-Integer Linear Programming
NPV	Net Present Value
RBU	Recovery Boiler Upgrade

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