THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Optimization of Process Integration Investments under Energy Market Uncertainties

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ISSN: 1404-7098 Publication 2008:4

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Printed by Chalmers Reproservice
Göteborg, Sweden 2008

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ABSTRACT

The increased climate concern in society puts pressure on industries to decrease their energy use in different ways, and a number of studies show that there is a large potential for improved energy efficiency in the energy-intensive industry, for example through process integration. Uncertainties about future energy prices and policy instruments make it, however, difficult to evaluate and compare different kinds of energy-saving measures with respect to net present value as well as reduction of CO_2 emissions.

This thesis presents a systematic methodology for optimization of investments in process integration under energy market uncertainty. The methodology, which also allows the timing of investments to be studied, is based on the assumption that investment decisions must be made before the outcome of uncertain parameters is known. In this way, the uncertainties are explicitly incorporated in the optimization model in a stochastic programming approach, and an investment plan that is robust to changes in the energy market can be obtained.

The uncertain parameters focused on in this thesis are electricity, wood fuel, and district heating prices, which are also indirectly affected by policy instruments such as the price of CO_2 emission permits and green electricity certificates. These uncertain parameters are modelled in a scenario-based approach where probabilities for the different scenarios have to be estimated. For the case study presented in the thesis, the probability distribution could, however, be varied substantially without altering the optimal solution.

Keywords: Process integration, stochastic programming, investment planning, scenario-based modelling.

List of publications

This thesis is based on the following papers.

I. Svensson, E., Berntsson, T., Strömberg, A.-B., Patriksson, M. (2008). An optimization methodology for identifying robust process integration investments under uncertainty. Accepted for publication in Energy Policy.

II. Svensson, E., Berntsson, T., Strömberg, A.-B. (2008). Benefits of using an optimization methodology for identifying robust process integration investments under uncertainty – A pulp mill example. Accepted for publication in Energy Policy.

III. Svensson, E., Strömberg, A.-B., Patriksson, M. (2008). A scenario-based stochastic programming model for the optimization of process integration opportunities in a pulp mill. Preprint - Mathematical Sciences at Chalmers University of Technology and University of Gothenburg, ISSN 1652-9715, no 2008:29. (This paper will soon be submitted for publication.)

Elin Svensson is the main author of all three appended papers. Thore Berntsson was the main supervisor. Ann-Brith Strömberg and Michael Patriksson co-supervised the work.

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1 Introduction

Decision-making in industry is a complex task, in particular for decisions regarding investments related to energy. The cost-effectiveness of industrial investments in energy efficiency is strongly related to energy market conditions such as electricity and fuel prices, CO_2 emissions permit prices, and other policy instruments. Due to the increased climate concern in society, these parameters are, however, highly uncertain. These circumstances call for a methodology where, unlike in traditional investment analyses, uncertain parameters are explicitly accounted for.

While researchers in many cases tend to identify the most far-reaching, visionary investment projects, decision-makers in industry, usually and for legitimate reasons, decide on the safe projects with short payback time but only relatively humble total energy savings. For industry, it would probably be more advantageous to employ a more long-term perspective if both technical and economic robustness of these kinds of investments were shown.

1.1 Background

Several studies show that there is a large potential for increased energy efficiency in the energy-intensive industry. The pulp and paper industry, being a large user of biomass, has an important role in greenhouse gas reduction, and is also the sector from which the case study presented in this thesis is taken. Surveys of the opportunities for cost-effective energy-efficiency measures and CO_2 reductions can be found in, for example, Martin et al. (2000) and Browne et al. (2001). A number of studies focus on heat integration in general (see e.g. Bengtsson et al., 2002; Towers, 2005; Axelsson and Berntsson, 2008) while others focus more specifically on the potential for green electricity production (Vakkilainen et al., 2004), the efficient use of biomass (Ådahl et al., 2006; Holmberg and Gustavsson, 2007), the reduction of CO_2 emissions including carbon capture and storage (CCS)

(Möllersten et al., 2003; Hektor and Berntsson, 2007), or for example energy-efficient technology (de Beer et al., 1998b).

Also in the iron and steel industry a large potential for energy savings has been identified (see e.g. de Beer et al., 1998a; Gielen and van Dril, 1999; Worrell et al., 2001; Larsson and Dahl, 2003; Oda et al., 2007). Refineries can be mentioned as an example of yet another energy-intensive industrial sector in which there is a potential for increased energy efficiency (Petrick and Pellegrino, 1999; Worrell and Galitsky, 2005; ITP, 2006).

Many of the above-mentioned studies show that energy savings can be achieved through a variety of measures, such as improved heat exchange, integration of heat and power (CHP) units, or heat pumping. There are, however, limitations on how different measures of this kind can be combined, and hence there is a need to compare the cost-effectiveness of different measures and combinations of measures in order to make the right decisions on investments.

Through the production of electricity, district heating deliveries, and imports or exports of fuel, industrial plants are closely connected with the constantly changing, surrounding energy market. The long-term economic outcome of an investment project is thus hard to evaluate. Furthermore, energy investments are often capital-intensive and have a long expected lifetime. During such long time spans, the energy market conditions are very likely to change, especially considering the assumed adoption of more stringent greenhouse gas targets. In order to pick the correct measures it is therefore important to consider the uncertainties of the future energy market conditions in the analysis of energy-efficiency investments.

Uncertainty regarding future energy market conditions will lead to ambiguous results concerning which energy-saving measures are most profitable. Electricity production is the best approach with high electricity prices while wood fuel export is better if wood fuel prices are high. If uncertainty considerations are included in a well-founded methodology for optimization of these investments, the decisions are more likely to be right. If no such methodology exists, there is a risk that all investments are postponed while waiting for more information on the development of the energy market, with lost energy-cost reductions and lost reductions of CO_2 emissions as a consequence.

1.2 Aims and objectives

This thesis makes up the first part of a research project about uncertainties in process integration studies. The overall objective of this project is to develop a methodology for the optimization of strategic investments for increased energy efficiency in industrial energy systems, considering uncertainties related to, for example, future energy prices and policy instruments, or new technologies.

The overall aim of the project is to show, by means of the proposed methodology, how to evaluate the large potentials for energy savings in an industrial energy system in view of the present uncertainties. The project also aims at illustrating the importance of making the right series of decisions in a long-term strategic perspective.

This thesis focuses on uncertainties related to future energy market conditions such as energy prices and policy instruments. The objectives of the thesis work are

- to develop a methodology for optimization of energy-efficiency investments under energy price and policy uncertainty, and
- to illustrate the use of the methodology in a case study.

The methodology should be based on existing methods and tools for the identification of measures and opportunities to increase energy efficiency as well as for optimization under uncertainty. The aim of applying the proposed methodology is an increased understanding of risks, opportunities and robustness related to strategic investment decisions, thereby yielding an improved basis for decision-making regarding such investments.

1.3 Papers

The thesis is based on three papers, of which Papers I and II constitute a series. Below, brief descriptions of the papers are presented.

> **Paper I** is the first article in a series of two dealing with the development of a methodology for the optimization of energy-efficiency investments under uncertainty. In this paper, a five-step optimization methodology is proposed.
>
> **Paper II** is the second article of the series which began with Paper I. Here, the proposed methodology is illustrated by a case study from the pulp and paper industry.

In **Paper III** the underlying mathematical optimization model used in Paper II is presented in more detail. The results from an extended case study are also further analyzed.

1.4 Thesis outline

This first chapter provides an introduction to the work carried out in this research project by giving a background and presenting the aims and objectives for the research. The next chapter presents related work, and ends with a section defining what makes the work presented here different from the related publications, and what thus makes up the contribution of this thesis.

Chapter 3 presents short introductions to the different research fields that the work of this thesis is based on, including process integration, stochastic programming, and some economic concepts.

The core of the research project – the developed methodology – is presented in Chapter 4. In Chapter 5 the methodology is illustrated in a case study. Results and conclusions specific to the case study are also presented in Chapter 5 while more general conclusions are given in Chapter 6. Chapter 7 finally presents some ideas for further research.

2 Related work

The work of this thesis includes process integration and stochastic programming applied to the optimization of investments under uncertainty. For references about process integration or stochastic programming, the reader is referred to Sections 3.1 and 3.2 respectively, where introductions to these two research fields are given.

2.1 Investment under uncertainty

The textbook *Investment under Uncertainty* (Dixit and Pindyck, 1994), was the first serious textbook on the theory of investment decision-making under uncertainty. This theory – the *real options* theory – explains how investment decisions are influenced by acknowledging, for example, the opportunity to wait for more information, or the value of flexibility. The real options theory is a good framework for understanding and discussing the modelling under uncertainty, and the real options problem can be solved, for example, by using stochastic programming.

2.1.1 Application to process integration

So far, the only attempts to study the effects of uncertainty when analyzing process integration investments have been based on post-optimization sensitivity analysis (see e.g. Karlsson and Söderström, 2002; Ådahl and Harvey, 2007). This kind of analysis does not recognize some important characteristics of the decision-making problem, and is therefore, in most cases, not an appropriate assessment method for the evaluation of investments under uncertainty (see also Section 3.2.2).

2.1.2 Application to energy-related investments

In the absence of published articles on investments in process integration under uncertainty, this section presents a number of publications dealing with investments under economic uncertainty in which the applications are related to energy and industry in some way.

Economic uncertainties have been incorporated in studies dealing with optimization of policy decisions on a national scale (see e.g. Birge and Rosa, 1996). More related to the work of this thesis are studies where the focus is on the decision-making at a specific plant or company. For the decision-makers in such cases, the energy market uncertainties are typically related to uncertain policy decisions that these decision-makers cannot affect. This type of investment decision has been subject to a number of studies regarding investment in electricity production in the power supply sector (Laurikka, 2006; Blyth et al., 2007; Fuss et al., 2008; Yang et al., 2008).

More related to industrial energy use is the study by Wickart and Madlener (2007), about the choice between combined heat and power production and heat-only production for an industrial firm, and the study by Diederen et al. (2003), on energy-price uncertainties aiming at explaining an observed energy-efficiency gap.

2.2 Relating previous work to the objectives of this thesis

With a slight reformulation, compared to Section 1.2, the first objective of this thesis work is to develop a methodology for the optimization of process integration investments under energy price and policy uncertainty. The second objective is to illustrate the use of the methodology in a case study.

The work of this thesis thus differs from the studies mentioned above in its application of optimization under uncertainty to process integration investments. A typical property of process integration measures is that they depend directly and indirectly on what other process integration measures have been implemented. This makes it impossible to associate cash flows with specific investment costs. While the optimization, as in the papers presented above, concerns investment under uncertainty, it also concerns the non-trivial problem of deciding which combination of energy-efficiency measures – out of a number of different opportunities – that should be realized.

3 Overview of background theory

This chapter presents a theoretical background to the work of this thesis. In the first section, the concept of process integration is introduced and related to the work carried out in this research project. The term *process integration* refers to systematic methods for optimization of production systems, primarily with respect to energy efficiency and reduction of environmental effects.

In this thesis, it is acknowledged that the optimization of investments in process integration is strongly dependent on uncertain energy market parameters. The framework used here to model the optimization under uncertainty is *stochastic programming*, which is introduced in the second section of this chapter. Stochastic programming is a field of optimization in which uncertainties that may influence the value of our decisions are explicitly accounted for.

The third section introduces some *economic theory*. The section begins with a discussion about barriers to and driving forces for energy efficiency. Then two important issues are addressed that have to be dealt with when evaluating investments which are made at different points in time, namely the net present value and the residual value of investments.

3.1 Process integration

Process integration methodologies always refer to *system-oriented* and *integrated* approaches, meaning that rather than optimizing process units separately, the interaction between different process parts is considered, and the system as a whole is optimized. In this thesis work, the system-oriented view is evident in the connection between the plant and the surrounding energy market. The system-oriented, integrated approach is also present in that all opportunities for energy efficiency are incorporated in the same optimization model. The consequences for other opportunities when making a decision are then directly accounted for.

Process integration methodologies can be *mathematical*, *thermodynamic*, and/or *economic*. In the methodology presented in this thesis, methods and tools from all these fields are incorporated. *Pinch analysis* is used to identify opportunities for improved energy efficiency (see Section 3.1.1); an economic investment assessment method, the *net present value*, is used to evaluate the identified opportunities (see Section 3.3.2); *mathematical programming*, finally, is used for the identification of the most robust and economically optimal combination of energy-efficiency investments (see Section 3.2).

3.1.1 Pinch analysis

Pinch analysis is a methodology based on the first and second laws of thermodynamics, which is used to target, for example, the minimum heating and cooling demands in process plants. Pinch technology refers to methods for synthesis of optimal process designs in relation to these targets. The basics of pinch analysis were presented in "User Guide on Process Integration" by Linnhoff (1982), who is one of the pioneers in the field. Revised versions of the user guide were published in 1994 (Linnhoff, 1994) and 2007 (Kemp, 2007). Review articles from Linnhoff and Smith – another member of Linnhoff's group at the University of Manchester – are also available (Linnhoff, 1993; Smith, 2000).

Pinch technology was first developed for the design of heat exchanger networks (Umeda et al., 1978; Linnhoff et al., 1979). Today, basic pinch technology has been extended and developed to incorporate a vast number of methods and tools. Some examples are the extension from grass-root design problems to retrofit situations (Tjoe and Linnhoff, 1986), methods for cost-effective retrofit designs (Carlsson et al., 1993), and methods for integration of, for example, separation processes (Kemp, 1986) or heat pumps (Wallin et al., 1990).

In this thesis, the results from a pinch study have been used as input. The study was published in a series of three articles (Axelsson et al., 2006a, 2006b; Olsson et al., 2006).

3.2 Stochastic programming

Stochastic programming is typically used for decision problems where the decision is made before the realization of some uncertain parameters and thus with imperfect information about the future. As a result, hedging against unfavourable outcomes of uncertain parameters leads to solutions having the best average performance.

In stochastic programming, the goal is to find a set of decisions that is feasible[1] for all possible outcomes of uncertain data and maximizes the expected value of some function of the decisions and the uncertain parameters. To calculate expected values, probability distributions for the uncertain parameters have to be known or estimated. In this thesis, the probability distribution is modelled as a discrete distribution with a finite number of possible outcomes of the uncertain parameters. This scenario-based modelling approach is further described in the next section.

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, 'decision – realization – recourse', is called a *two-stage recourse* problem. 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 (Dantzig, 1955), initialized by George B. Dantzig, one of the founders of the whole field of linear programming and the inventor of the famous Simplex method. Later, a number of books have been published, covering the theory of stochastic programming (see e.g. Kall and Wallace, 1994; Birge and Louveaux, 1997; Ruszczyński and Shapiro, 2003; Kall and Mayer, 2005). The reader is also referred to a tutorial by Sen and Higle (1999), and a review article by Birge (1997).

The model used in this thesis is a mixed-integer linear programming (MILP) model (see also Section 4.1.1). Stochastic MILP is an active field of research which has been discussed in a number of works during the last decade (see e.g. Klein Haneveld and van der Vlerk, 1999; Römisch and Schultz, 2001; Louveaux and Schultz, 2003; Ruszczyński and Shapiro, 2003; Schultz, 2003; Sen, 2005).

3.2.1 Scenario-based modelling

Figure 1 shows an example of a *scenario tree* with four stages and two possible realizations at each stage. Every node *n* in the scenario tree corresponds to a specific realization of uncertain parameters at a specific stage.

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

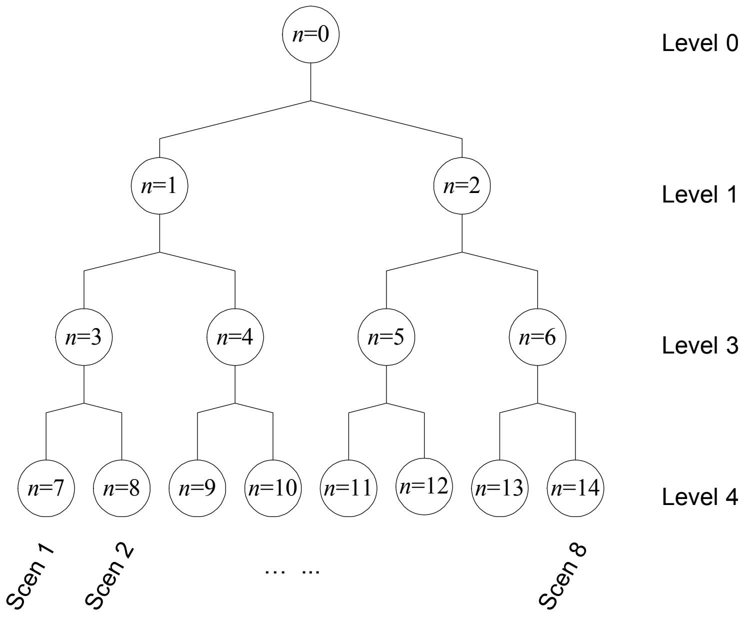


Figure 1: *An example of a four-stage scenario tree.*

Node $n = 0$ is called the *root* and corresponds to the known state at the beginning of the process. Each new level of nodes in the scenario tree is a new stage in the decision process. A *scenario* refers to the realization of a root-to-leaf path in the tree. 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.

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.

3.2.2 Relation to sensitivity analysis

A traditional method for analyzing relations between inputs and the output of a model is *sensitivity analysis*. According to Saltelli et al. (2004), "sensitivity analysis is the study of how the variation [uncertainty] in the output of a mathematical model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variation in the input of a model". The sensitivity analysis approach is recommended by standard textbooks in, for example, chemical engineering design (see e.g. Sinnott, 1999, p. 273), but also by literature on linear programming (see e.g. Nash and Sofer, 1996, pp. 435-437).

A sensitivity analysis answers questions about how sensitive the optimal solution is to variations in input data and gives an estimate of the risk involved in the investment project. It can also be used to determine which parameters affect the solution the most. Sensitivity analysis is, however, not sufficient when optimizing decisions that are made under uncertainty (Wallace, 2000). Stochastic programming should instead be the preferred choice of method. In stochastic programming, unlike sensitivity analysis, it is acknowledged that decisions must be made before the actual parameter values become known (see Section 3.2). This has important consequences for the possibilities of finding the truly optimal solution to the decision problem under uncertainty.

A sensitivity analysis will never result in a solution for which there is a cost related to flexibility. In reality, however, these solutions are often the best ones, providing a way to hedge against uncertainty. This kind of flexible solutions – in addition to all solutions found using sensitivity analysis – can, however, be found using stochastic programming. Furthermore, while sensitivity analysis can produce a number of different solutions to an optimization problem, stochastic programming provides a way of choosing which one of the solutions is optimal overall.

3.3 Economic theory

Some motivation to the work carried out here is provided from the field of organizational economics, or more specifically *barriers to and driving forces for energy efficiency*. Then quick reviews of the concepts of *net present value* and *residual value of investments* are provided.

3.3.1 Barriers and driving forces

There is a large potential for improved energy efficiency in industry (see Chapter 1, p. 1–2). A number of reasons can be given for why this potential has not yet been explored to a larger extent. Mainstream economic theory uses the term *barriers to energy efficiency* to explain the so-called energy-efficiency gap. *Driving forces* are different factors that promote the implementation of cost-effective energy-efficiency investments. The Swedish pulp and paper industry, being the framework of the case study in this thesis, will serve as an example also for the discussions about barriers and driving forces.

One of the main driving forces for energy efficiency in Swedish pulp and paper industry is a long-term energy strategy (Thollander and Ottosson, 2008). However, most traditional investment rules are not suited for long-term planning. Neither is there a way to account for variations in, for example, future prices, nor is the possibility of delaying investments or making new investments later acknowledged.

The list of barriers to energy efficiency presented by Thollander and Ottosson (2008) did not include uncertainty in future energy market conditions. However, they only investigated barriers to energy-efficiency investments which are "cost-effective from the company's point of view". Since traditional investment rules cannot account for expected future energy price rises, some investments were judged as not cost-effective and therefore excluded from the study. Nevertheless, these investments can be cost-effective in a long-term perspective. Hence, although uncertainties related to rising energy prices are generally considered to be a driving force towards energy efficiency, they could also be considered a barrier if investment rules are applied which do not account for such expected future changes.

Furthermore, if there are uncertainties regarding the relation between, for example, electricity and wood fuel prices, the comparison of different kinds of energy efficiency investments becomes complicated. As a result, major investments are usually postponed while waiting for better information regarding the future energy market.

As can be understood from the above discussion, there is a need for a well-founded approach to assess the investment planning in order to obtain a better basis for decision-making. Such an improved basis for decisions can also be considered a driving force for investments in energy efficiency. A methodology which adopts a systematic approach to long-term strategic investment planning is therefore needed, both because long-term energy planning is a driving force for energy efficiency, and because uncertainties regarding the future energy market could be considered a barrier to energy efficiency when traditional investment rules are applied.

3.3.2 The net present value

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

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

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 is given to future cash flows. Hence, 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.

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 which results in the highest positive NPV. Hence, 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 to wait or make alternative investments are termed *real options* (see e.g. Dixit and Pindyck, 1994).

3.3.3 The residual value of investments

Since we allow investments to be made at different points in time, there will be a point where the lifetimes of some investments have expired while others are expected to be profitable for yet a number of years.

Assume that all investments considered have an expected lifetime of 30 years. Assume further that one investment is made at $t = 0$, and another is made at $t = 15$. If we limit the calculation period to 30 years, the revenues for the first investment will be counted for the full lifetime while the revenues for the second investment will be counted only for half the lifetime. This, naturally, causes an unfair comparison between the two investments. There are, in principle, two ways of dealing with this situation:

- The calculation horizon can be extended beyond 30 years.
- The second investment can be given credit for expected revenues after the end of the calculation horizon, that is, it can be assigned a residual value.

Using the first approach, the net cash flows associated with the first investment will have to be evaluated after its economic lifetime. There are then a number of possible situations:

- The lifetime of the investment turns out to be longer than expected. The equipment invested in is still perfectly working and the revenues are the same as during the lifetime.
- The maintenance costs of the ageing equipment are becoming substantial. Repairs are needed more often and shutdowns are getting more frequent.

Depending on the type of investment the costs of such shutdowns can range from negligible to substantial.

- The equipment has to be replaced, possibly generating a scrap value. It can be replaced by the same type of equipment or by something else.

It is, in practice, impossible to judge 30 years in advance, which will be the situation for each investment considered, and the differences in net cash flows are enormous between the different alternatives.

This leaves us with the second approach, which means that the calculation horizon should be at most the length of the economic lifetime of the investments, and the residual value of the later investments has to be estimated. The actual residual value of these investments is given by the expected future net cash flows. These obviously cannot be evaluated after the calculation horizon. The proposed approach is therefore to choose the residual value to exactly cancel out the annualized investment cost for the remaining years of the investment lifetime (see Appendix for details). This corresponds to a net present value being equal to zero for the remaining years, which could be interpreted as indifference to whether the investment should be made or not.

This way of dealing with the residual value is needed simply because no better approach exists. The more time remaining of an investment lifetime when the calculation horizon ends, the higher is the impact of any erroneous assumptions on the results. Hence, in the optimization model, only investments for which a substantial part of the lifetime lies within the calculation horizon should be allowed.

4 Methodology

This chapter presents the core of this thesis work – the methodology for optimization of process integration investments under uncertainty. The idea of the proposed methodology is that methods and tools for identification of energy-efficiency measures in process industries are combined with mathematical models and methods for optimization under uncertainty.

First, a description of the developed optimization model is presented. This model is central for the optimization of investments under uncertainty. The second part of this chapter presents a five-step methodology, which should be regarded as a guide to the use of the optimization model regarding input data, constraint formulation, and result analyses.

4.1 The general optimization model

The objective of the optimization model is to find the combination of investments which results in the highest NPV (see Eq. (1)). To account for uncertainties, the expected value of NPV over all scenarios is maximized. The investment decisions are required to be made before any outcomes of the uncertain parameters are known.

We introduce the notation S for the set of all scenarios s and let p_s be the probability for scenario s to occur. The decision variables which are associated with the initial investments are contained in the vector x_0 and the decision variables corresponding to a scenario s, representing, for example, later investments and operating plans, are elements of the vectors x_s. The vector x_0 and the vectors x_s are gathered in the decision vector x. Further, we introduce the initial investment cost C_0 to be a function of the decision variables x_0, and the net cash flow in year t, C_t, to be a function of the decisions x and the uncertainty parameters ω_s for scenario s. The objective function is then to

$$\text{maximize } \mathrm{E}[\mathrm{NPV}(x)] \coloneqq -C_0(x_0) + \sum_{s \in S} p_s \sum_{t=1}^{T} \frac{C_t(x_0, x_s, \omega_s)}{(1+r)^t}, \tag{2}$$

where E denotes expectation. The net cash flow of the final year, C_T, should be adjusted for the residual value of the investments (see Section 3.3.3).

The above notation follows the notation used in the first two articles appended to this thesis. In the third article a more detailed model description is presented, and the notation is more extensive. A summary of the differences in notations is given in Table 1.

Table 1: *Differences in notations between the simple and extensive formulations.*

Property	**Simple formulation** Used in thesis and in Papers I and II	**Extensive formulation** Used in Paper III
Decision variables	All gathered in the vector x	Different notation for different types of decisions
Costs and cash flow functions	C_0 and C_t	Divided into several functions for costs, revenues, etc
Scenario reference	To scenario s	To node n of the scenario tree
Uncertainty parameters	Denoted by ω_s	Denoted by ξ^n
Time scale	One year t	A couple of years ℓ

The decisions x are limited by a number of constraints and requirements. Some of these constraints are general and are valid in different applications and case studies, while others are case-specific and need to be formulated with respect to the specific case at hand.

The general part of the model consists of constraints for the relations between decisions and investment costs, energy savings, and resulting output when the energy savings are used for cost savings. The resulting output can be the amount of electricity generated in a turbine, decreased fuel imports, or the amount of heat delivered to a district heating network. The net cash flow can then be computed as a function of the output for these options.

Paper III gives a detailed description of the model formulation including both general constraints and constraints specific to case study, which is described in Chapter 5.

4.1.1 Model properties – integer variables and linear functions

The decisions which are to be optimized in a process integration study are basically engineering design decisions. As such, they typically involve simulations, experimental data, and catalogue selections to establish the relations between the decision variables and the dependent characteristics and attributes of the design. These relations are, in practice, impossible to express as analytical continuous functions. Because of this undesirable property, the decision variables are instead modelled as integer or binary, expressing a choice between discrete options. For the finite number of discrete options, the dependent characteristics can then be established in advance.

The introduction of integer or binary variables into the optimization model increases its computational complexity and thus the solution time. The scenario tree modelling of the random variables further increases the size of the problem.

Nonlinearity of the functions describing the relations in the model would further increase its computational complexity and thus increase its solutions time, especially since many of the nonlinear functions probably would be non-convex. Since integer variables are difficult to avoid in this type of model (that is, either an investment has to be taken completely or not at all), we therefore require the functions in the optimization model to be linear. The final model will then be a mixed-integer linear programming (MILP) model, which can be solved using commercial solvers such as CPLEX (ILOG, 2006).

4.2 The five-step methodology

The tasks required to arrive at an applicable model formulation have been summarized in a five-step methodology. Figure 2 illustrates Steps 1–5 as parts of a framework where process integration, energy market modelling, and optimization are key concepts.

Process integration is the basis of the methodology and is used to identify what should be included in the model in terms of opportunities for improved energy efficiency. The systems perspective which, by definition, is an important aspect of process integration is closely related to the development of an energy market scenario model which is relevant to the system analyzed. Understanding of process integration is needed also in the last step for analyzing the results and drawing the right conclusions. Next, a description of the steps of the methodology is presented.

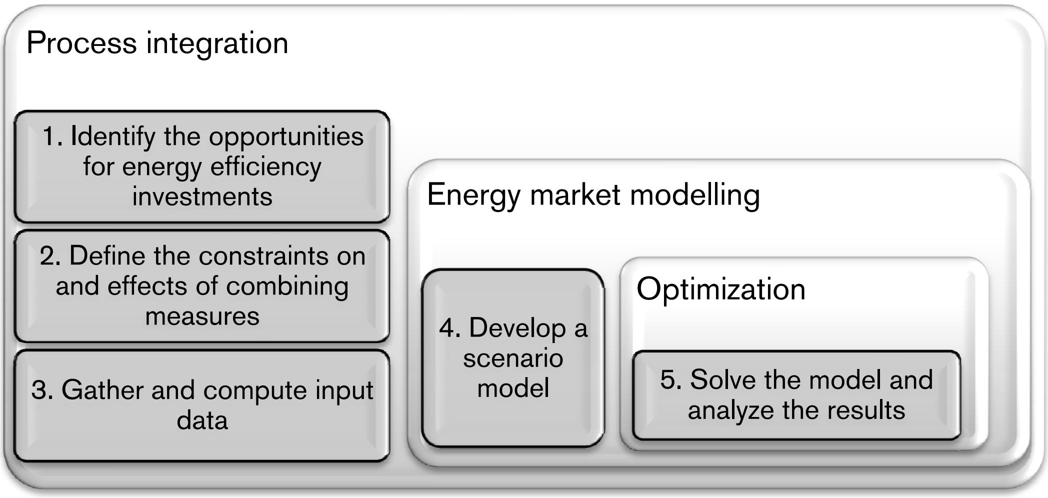


Figure 2: *Illustration of the five-step methodology and the relation to different areas of research.*

4.2.1 Steps 1-3: Process integration

In the first steps, process integration methods such as pinch analysis are used to identify and characterize opportunities for cost savings through increased energy efficiency of the plant considered. Energy-efficiency measures can be, for example, improved internal heat exchange for the reduction of heating and cooling utilities, more energy-efficient equipment such as efficient drying or separation processes, and more efficiently integrated units by using, for example, excess heat for distillation or evaporation, or heat pumps for increased heat recovery. There is also a wide range of more sector-specific energy cost-saving measures. All relevant measures should be characterized with respect to their associated investment costs and resultant energy savings.

The energy-saving measures enable energy cost savings, which can be accomplished, for example, through increased electricity generation in steam or gas turbine combined heat and power (CHP) plants, through decreased fuel imports or fuel switching, or through heat integration with nearby communities or industries through district heating. CO_2 capture and sequestration might also be a way to accomplish cost savings, although still under development and therefore associated with uncertainties regarding investment costs and availability. In addition to data on costs and energy savings, data relating the energy savings to, for example, the electricity output of a turbine are needed.

An important aspect of process integration is that different measures are not usually additive and their connections are complicated. A cooling demand at the plant might also be regarded as excess heat, which can be used, for example, in a heat pump or for district heating. Increased heat exchange at the plant will decrease the heating demand, but also reduce the excess heat and thereby the potential for heat pumping and district heating. Logical and quantitative constraints describing these connections between measures therefore constitute an important part of the mathematical model.

4.2.2 Step 4: Scenario modelling

The scenario model (see Section 3.2.1) should contain the price data necessary for economic evaluation of the process integration options. The presence of electricity certificates and/or CO_2 emissions permits is also important to consider.

The characteristics of the uncertainties related to these parameters make it, in practice, impossible to completely describe the set of possible future scenarios. The scenario model is therefore kept simple. Different energy market parameters are strongly correlated. Hence, the scenario tree is best constructed from a number of consistent energy market parameter sets, or building blocks. A tool for generating such energy market parameter sets has been developed by Axelsson et al. (2007). The parameter values corresponding to each node n of the scenario tree will then be given by one such parameter set.

A root-to-leaf path through the scenario tree forms a scenario, which is built from a series of building blocks. This type of development paths is recognized from work by Ådahl and Harvey (2007). The model requires an estimate of the probability of each of these paths to occur. Hence, there is a need for simplification and a limited number of such paths. The advantage of using many scenarios – to cover many future possibilities – has to be weighed against the disadvantages of having to estimate the probability for each of the scenarios to occur and ending up with a very large-size optimization model.

The time scale of the scenario model is important. For example, in year 2020, electricity is assumed to be traded on a single common North European market, while today only the Nordic market is relevant to consider for Swedish conditions. Furthermore, in the near future, even though higher emissions charges are promoting new technologies for electricity production, the marginal production will not have had time to change, and new technologies might not yet be available.

4.2.3 Step 5: Analyzing optimization results

The solution to the optimization model is the expected optimal investment plan considering the scenario model of the uncertain future energy market. The solution value (the NPV) will, in most cases, vary substantially for different sets of economic parameters, for different scenarios, etc. However, if the characteristics of the optimal solution, that is the investment plan, are unchanged the solution is still robust.

Understanding of process integration and process technology is needed to judge whether the optimal solution is possible to implement. An interactive, iterative procedure is in many cases needed here. The introduction of new constraints might, for example, be necessary in order to avoid unwanted combinations of investments or operating conditions that are difficult to control. Much can be learned, however, by also considering the solutions which at first seem unreasonable. These can often give a hint to where flexibility is bringing most benefit.

The results can be analyzed in a number of ways by varying different input data. Assuming that the process data are deterministic, the most interesting analyses are probably connected with the scenario modelling and the economic parameters, which are both, in a way, subject to opinion. The stability of the solution, in terms of the importance of making fair assumptions about the probability, can for example be investigated by varying the assumed probability distribution. Another analysis is made by investigating the difference between a short-term perspective and a long-term strategic perspective by adjusting the economic lifetime and the discount rate.

5 Case study

A new methodology for optimization of process integration under energy market uncertainty has been developed. This chapter presents a case study in which this methodology has been used. The aim of the case study was to test and discuss the proposed methodology and its use as a decision support tool for investment planning under uncertainty.

The case study, taken from the pulp and paper industry, is carried out for a computer model of a typical Scandinavian chemical pulp mill. The model mill was originally developed for the Swedish national research programme ‘The Future Resource Adapted pulp Mill’ (FRAM, 2005). In this case study, the mill is assumed to be faced with a planned increase of the pulp production by 25% in the near future.

This chapter gives an overview of the studied case. First, in Section 5.1, a description of the analyzed pulp mill is presented. This section discusses the process integration opportunities that are found in the mill and is thus associated with Steps 1–3 of the proposed optimization methodology (see Section 4.2.1). Section 5.2 deals with the economic conditions assumed in the study, including the model of the surrounding energy market, which corresponds to Step 4 of the proposed methodology (see Section 4.2.2). Associated with Step 5 of the methodology are Sections 5.3 and 5.4 which present the results and conclusions from the case study (see Sections 4.2.3).

5.1 Description of the analyzed pulp mill

Chemical pulp is produced by mixing wood chips and chemicals in so-called pulp digesters where heat and chemicals are used to separate the cellulose fibres from lignin, which is the material that binds the cellulose fibres together. The liquor containing the lignin and the used pulp digesting chemicals is called black liquor. After the black liquor has been concentrated in an evaporation plant, it is used as 'fuel' in a recovery boiler. In the analyzed mill, as in many others, no additional fuel needs to be imported. The steam from burning the black liquor in the recovery boiler is enough to cover the demand of the process, making the recovery boiler a central part of the energy system at the mill.

The purpose of the recovery boiler is to recover the black liquor chemicals and to recover the energy of the lignin. The energy is utilized to produce high-pressure steam which is used to cover the steam demand of the pulping process. Most of the process steam demand is at low pressures. Electricity can therefore be generated by passing the high-pressure steam through a back-pressure turbine to the lower pressure.

The following description of the analyzed mill is, if no other references are given, based on a previous study of a production increase at the model mill (Axelsson et al., 2006b). Axelsson et al. (2006a) used pinch technology to identify opportunities for steam savings at the studied mill. If a steam surplus can be achieved it can, for example, be used for electricity production or lignin extraction (Olsson et al., 2006), or for district heating (Jönsson and Algehed, 2008).

The recovery boiler is often a limiting part of the process – a bottleneck. A production increase will lead to an increase of black liquor flow to the recovery boiler, but also to an increased steam demand of the process. In principle, there are two approaches for debottlenecking of the recovery boiler: a recovery boiler upgrade (RBU) or lignin separation. These two approaches are described in the following section, after which the conditions for district heating (DH) deliveries and finally the opportunities for process integration are discussed.

5.1.1 Debottlenecking of the recovery boiler

Figure 3 illustrates the two approaches to increase the production when the recovery boiler is a bottleneck. In the first approach, the recovery boiler is upgraded to meet the new capacity requirements (see Figure 3a). The investment cost of such an investment is substantial. However, since more high-pressure steam can be produced in the upgraded boiler, there will be an opportunity to increase the electricity production.

In this approach, if investments are made to decrease the process steam demand, there will be a surplus of low-pressure steam at the mill. This steam can be used for electricity production in a condensing turbine, or it can be delivered as district heating.

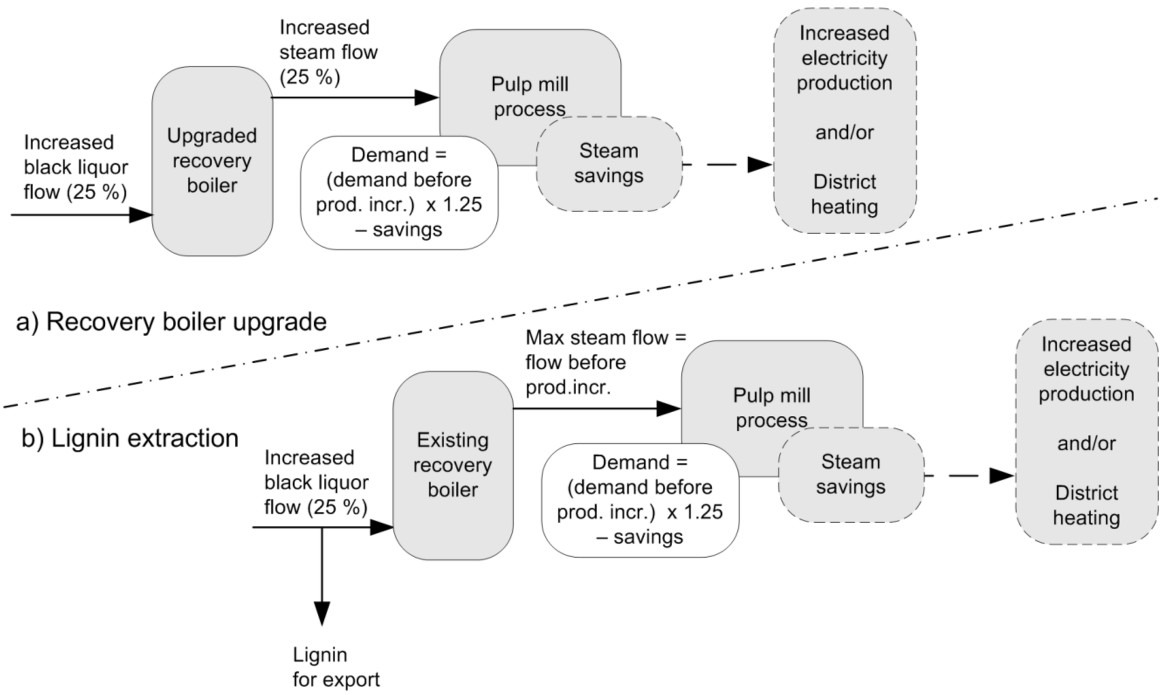


Figure 3: *Two approaches to increase the production when the recovery boiler is a bottleneck: a) Upgrading the recovery boiler to handle the new capacity requirements. b) Separating lignin from the black liquor to decrease the load on the recovery boiler.*

The expensive recovery boiler upgrade (RBU) can be avoided if the fuel input to the recovery boiler is decreased by separating lignin from the black liquor (see Figure 3b). The lignin can, for example, be exported as a wood fuel. Because of the production increase, the steam demand of the process will increase if no other process changes are made. In the lignin separation approach, however, the steam production cannot be increased since the old recovery boiler is kept. This makes steam savings necessary to keep the steam demand at the same level as before the production increase. In that case, lignin separation becomes an interesting option.

Further steam savings might, also in the approach with lignin extraction, make it possible to achieve an energy surplus at the mill. If this is the case, electricity production and/or district heating can be of interest also in this approach. The reader is referred to Olsson et al. (2006) for more theory concerning lignin separation and its overall consequences for the energy system of the mill.

5.1.2 District heating

The potential for and profitability of district heating (DH) deliveries are dependent on the district heating demand and the alternative heat production in district heating systems near the pulp mill. Generally, the potential for profitable excess heat cooperation between mills and energy companies is higher in small district heating systems than in larger systems (Jönsson et al., 2008). Here, we therefore assume that a small district heating system exists near the mill. The data for a typical such district heating system are taken from a study by Svensson et al. (2008). District heating can be produced from low-pressure (LP) steam, hot water, or warm water if it is heat-pumped to an adequate temperature.

5.1.3 Process integration opportunities

There are several opportunities to save steam at the studied mill. A complete list of the measures included in the case study can be found in Paper II. A detailed description of the pinch analysis is found in the articles describing the original study on the model mill (Axelsson et al., 2006a, 2006b; Olsson et al., 2006). Data for the mill including conditions for electricity production, lignin extraction and district heating, are given in Paper II, but also in Paper III where they are presented in the form of their input to the optimization model.

Not all of the identified measures can be combined. The restrictions on combinations of the measures are formulated in words in Paper II and mathematically in Paper III. Next, a few examples are presented to exemplify the difference between easily formulated constraints and more complicated ones.

Three of the identified steam-saving measures are the new three-stage flash, the process-integrated evaporation plant (PIvap), and the rebuilt hot and warm water system (HWWS). Examples of easily formulated constraints are that the new 3-stage flash (Flash) cannot be combined with process-integrated evaporation (PIvap), and that the hot and warm water system (HWWS) has to be rebuilt in order to install PIvap. These constraints are given by

$$\begin{aligned} x_{\mathrm{PIvap}}^{n} + x_{\mathrm{Flash}}^{n} &\leq 1, \qquad n \in N, \\ x_{\mathrm{PIvap}}^{n} - x_{\mathrm{HWWS}}^{n} &\leq 0, \qquad n \in N, \end{aligned} \tag{3}$$

where x_m^n is a binary variable that takes the value 1 if measure m has been implemented before node n in the scenario tree (see Figure 1), and the value 0 otherwise.

A number of different evaporation plant designs are included in the model. One difference between designs is whether or not the plant is adapted for lignin extraction. One more complicated constraint expresses that if the evaporation plant is designed for lignin extraction, lignin has to be extracted by an amount that equals the design capacity of the evaporation plant.

First, the variables λ^n and $\hat{\lambda}^n$ have to be introduced. These variables represent the existing and added lignin extraction capacity, respectively, for the evaporation plant in node n. The evaporation plant extraction capacity λ^n should be fixed except when the evaporation plant is rebuilt, and the actual lignin extraction rate α_{LIG}^n should equal the design capacity of the evaporation plant. This is most easily expressed by the following constraints:

$$\begin{aligned} &\lambda^0 = 0, && \\ &\lambda^n = \lambda^{p(n)} + \hat{\lambda}^{p(n)} \hat{x}_{EvapLig}^n, && n \in N, \\ &\lambda^n = \alpha_{LIG}^n, && n \in N, \end{aligned} \tag{4}$$

where $p(n)$ refers to the parent of node n (see Section 3.2.1) and $\hat{x}_m^n$ takes the value 1 if an investment in measure m is made in node n and the value 0 otherwise. The above formulation, however, is not consistent with the required linearity of the model (see Section 4.1.1) since it includes the multiplication of the lignin capacity variable $\hat{\lambda}^{p(n)}$ and the investment decision variable $\hat{x}_m^n$. Avoiding the multiplication of variables and expressing the same behaviour using linear functions requires that the constraints (4) are replaced by the constraints

$$\begin{aligned} \lambda^0 &= 0, && \\ \lambda^n &= \lambda^{p(n)} + \hat{\lambda}^{p(n)}, && n \in N, \\ -M_{LIG} \hat{x}_{EvapLig}^n \le \hat{\lambda}^n &\le M_{LIG} \hat{x}_{EvapLig}^n, && n \in N, \\ \lambda^n - M_{LIG}\left(1 - x_{EvapLig}^n\right) \le \alpha_{LIG}^n &\le \lambda^n, && n \in N \backslash R. \end{aligned} \tag{5}$$

Here, we also use the binary variable x_m^n, which was defined above as being 1 if measure m has been implemented before node n in the scenario tree, and 0 otherwise. The parameter M_{LIG} is a 'sufficiently big' number to make some of the above constraints redundant when M_{LIG} is multiplied by 1.

5.2 Economic conditions

The evaluation of process integration measures depends strongly on the economic assumptions made. This section begins with a description of the objective function value, that is the net present value of the investments, and explaining of what is included in this value. After that, a discussion follows on the choice of economic parameters, such as the economic lifetime and the discount rate. Finally, the important energy market scenario model is presented.

5.2.1 Economic evaluation

The objective of the optimization is to find the combination of an approach to production increase and process integration investments which yields the highest net present value (see Eq. (1)). In order to increase the pulp production at the mill by 25%, a number of other processes of the mill have to be upgraded in addition to the upgrades related to debottlenecking of the recovery boiler. These investments would be the same for both approaches, and so would the revenues from the increased pulp production. The net present value for the production increase can then be defined as

$$\mathrm{NPV}(\textit{production increase}) = \mathrm{NPV}(\textit{fixed}) + \mathrm{NPV}(\textit{options}),$$

where NPV(*fixed*) refers to the NPV of all the cash flows that are the same regardless of which approach and which process integration measures are chosen, and NPV(*options*) refers to the NPV of all the cash flows that are dependent on the decisions made. Since NPV(*fixed*) is a constant, it can be excluded from the objective function without changing the optimal solution. The objective function used here is therefore to maximize NPV(*options*). Although the same optimal solution is achieved using either NPV(*production increase*) or NPV(*options*), it should, however, be noticed that the values of the solutions will differ.

5.2.2 Economic parameters

Investment decisions in industry today are usually based on investment criteria demanding short payback times. There is, however, an awareness of the need for strategic decisions in the presence of the uncertain energy market conditions that the mills are faced with today. In a longer perspective, future energy prices and policy instruments are increasingly difficult to estimate and the need for a systematic approach to analyze investments under uncertainty becomes more pronounced.

The economic parameters needed for the calculation of the net present value are the economic lifetime of the investments and the discount rate (see Section 3.3.2). Within the research programme FRAM which is a cooperation between the Swedish Energy Agency and industrial partners, an annuity factor[2] of 0.1 has been identified as reasonable for strategic decisions (FRAM, 2005). As a base case, an economic lifetime and a discount rate has therefore been used that result in this value of the annuity factor.

[2] The annuity factor $a = r/(1-(1+r)^{-T})$, where r is the discount rate and T is the economic lifetime.

5.2.3 The energy market scenario model

The uncertain energy market is modelled as a scenario tree (see Sections 3.2.1 and 4.2.2). Each node of the scenario tree should be associated with a consistent set of energy market parameter data – a scenario building block. The following list presents the four blocks used in this case study.

Block I – The Swedish energy market in the near future.

Block II – A 'business as usual' (BAU) evolution of society.

Block III – A 'moderate change' evolution of society.

Block IV – A 'sustainable' evolution of society.

Data for the blocks are given in Table 2.

Table 2: *Energy market parameter sets for the four scenario building blocks.*

	Scenario block			
	I	**II**	**III**	**IV**
Input data				
Price crude oil [USD/barrel]	62	62	62	62
Price natural gas [USD/Mbtu]	8.0	8.0	8.0	8.0
Price coal [USD/tonne]	55	60	60	60
CO_2 charge[3] [€/tonne]	26.6	26.6	34.6	42.6
Price green elec. certificates [€/MWh_{el}]	21.7	16.0	10.6	5.3
Price green transp. certs. [€/MWh_{fuel}]	0	0	0	0
Electricity prices [€/MWh_{el}]				
Electricity (marg. cost incl. CO_2)	38.6	57.3	60.8	61.9
Elec. incl. green cert.	60.3	73.3	71.4	67.2
Wood fuel prices [€/MWh_{fuel}]				
Forest by-products	13.0	15.3	17.9	20.7
Pellets = 1.75 × price of by-products	22.1	26.7	31.4	36.2
Lignin = 1.5 × price of by-products[4]	19.5	22.9	26.9	31.0
District heating prices [€/MWh_{heat}]				
Cost for alt. DH prod. (bio. boiler)	28.4	33.7	39.3	44.9
Mill excess heat = 0.75 × alt. prod. cost	21.3	25.3	29.5	33.7

[3] The CO_2 charge can either be in the form of a price for emission permits in a cap and trade system, or in the form of a tax.

[4] There is no market price for lignin at the moment. Axelsson and Berntsson (2008) assume that the price will be 35% higher than that of by-products. Here, a slightly higher value is chosen such that the case study clearly illustrates our methodology.

The blocks II–IV were generated using a tool developed by Axelsson et al. (2007)[5]. Block I is based on Swedish conditions from the first quarter of 2006. As can be seen, the electricity price including the green electricity certificates is quite similar between the blocks (with the exception of Block I). Part of the reason is that the green electricity certificates are assumed to drop in price when the CO_2 charge is increased, because the CO_2 charges also promote green electricity production (Axelsson et al., 2007). The effect is that the increase in CO_2 charges and the decrease in green certificates cancel out and that the electricity price is almost unchanged. A system with green electricity certificates is in force in Sweden and some other European countries today. Electricity production at the mill is based on biomass and is therefore granted electricity certificates.

Apart from the electricity prices, lignin and district heating prices are necessary parameters in the optimization model. The values for these prices are calculated based on the prices of forest by-products, which are given as output from the scenario-generating tool.

In accordance with the methodology described by Ådahl and Harvey (2007), a number of possible development paths are constructed based on the parameter building blocks described above. The development paths, or scenarios, are illustrated as a scenario tree in Figure 4. In Paper II, five different probability distributions for the scenarios, here denoted by PD1–PD5, were used (see Table 3). In Paper III, a uniform probability distribution was used in the base case. This distribution was then changed in order to investigate how high the probability for a single scenario can be before there is a change in the optimal solution.

Table 3: *Path probabilities for five different distributions.*

[%]	PD1	PD2	PD3	PD4	PD5
BAU	25	5	16	5	5
M1	25	10	17	30	15
M2	20	15	17	15	15
S1	15	20	17	30	30
S2	10	25	17	15	30
E	5	25	16	5	5

[5] This tool is developed to generate energy market parameter sets for year 2020, assuming a North European electricity market, where CCS is a fully developed technology. Here, this tool has been used also for the near future, which will make some of the acquired results doubtful. The purpose of the case study is, however, primarily to serve as an illustration of the methodology, which it still does.

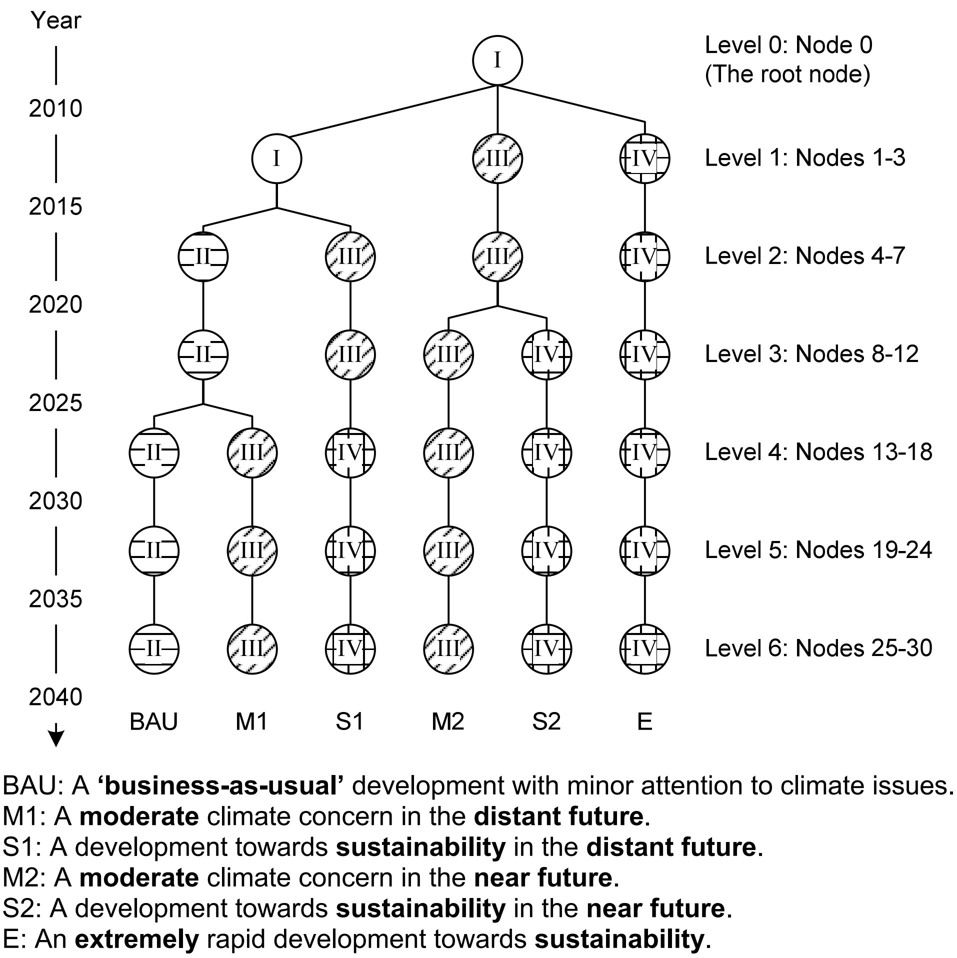


Figure 4: *Scenario tree for energy market parameters.*

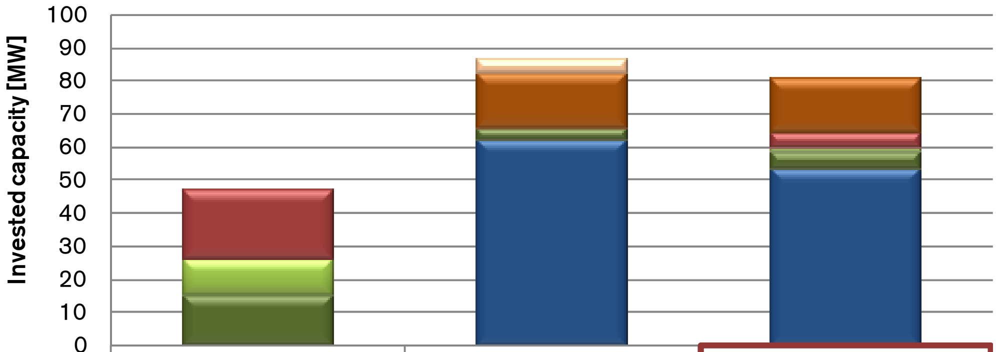
5.3 Results

This section presents the results from applying the proposed methodology to the case described above. First, some general results will be presented, after which follow a few sections with additional analyses.

5.3.1 General results

As a base case, the economic lifetime was set to 30 years and the discount rate to 9% corresponding to an annuity factor of 0.1. In Paper II, the model was solved for the five different probability distributions PD1–PD5 (see Table 3). The computation time to find an optimal solution was about one minute (see Paper III for more details).

The optimal solution under uncertainty, using each of these five distributions, is characterized by just enough lignin being extracted to avoid upgrading the recovery boiler. Additional steam savings are used for electricity production and district heating. The model was also solved for one path in the scenario tree at a time, that is, with 100% probability for one path and 0% probability for the others (corresponding to a traditional sensitivity analysis). In all solutions obtained, all investments are made immediately. Only four different solutions arise and investments in steam savings are similar for all four solutions. The initial invested capacity for the solutions, except for investments in steam savings, is presented in Figure 5, which also indicates the optimal solution for each scenario[6].



	RBU + turbines	Max lignin	Just enough lignin
DH from 60°C heat	0	4.6	0 (0)
DH from 100°C heat	0	16.3	16.3 (16.3)
DH from LP steam	20.9	0	4.6 (4.6)
Condensing turbine	11.4	0	1.4 (0.9)
Back-pressure turbine	15.1	3.8	5.3 (4.8)
Lignin separation plant	0	62.4	53.6 (56.6)
Optimal solution for:	BAU, M1	E	PD1–PD5, M2, S1, (S2)

Figure 5: *The main investment alternatives and their characteristics. Invested capacity refers to capacity exceeding the existing capacity of the mill.*

The value of the solutions, that is, the NPV of the investments, is illustrated in Figure 6. Here, the path that turns out to be the true development is called the realized path. Thus, the leftmost group of bars (four blue bars and one red bar) illustrates what will be the resulting NPV if reality turns out to follow a BAU scenario. The next group of bars illustrates different solutions when M1 is the realized path, and so on.

[6] The solution which is optimal for scenario S2 is very similar to the 'Just enough lignin' solution and is therefore only presented with numbers in brackets, not explicitly in the figure.

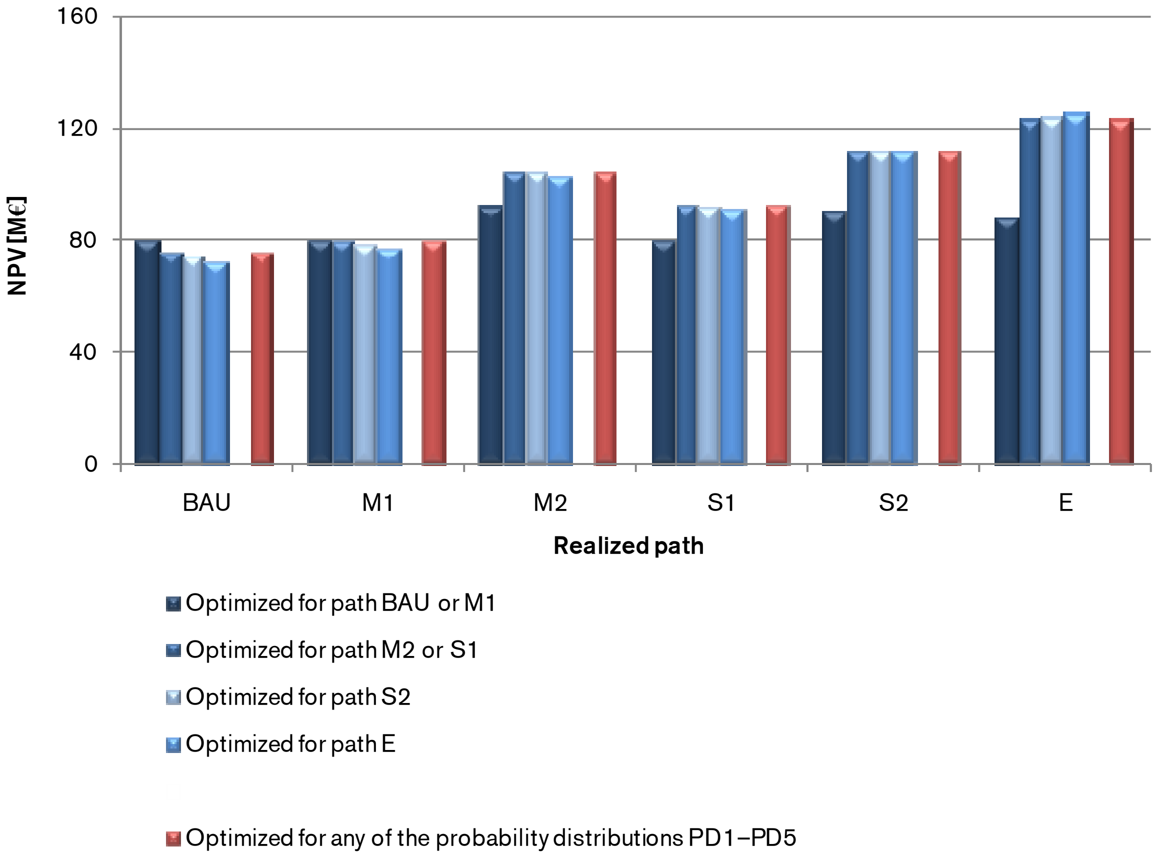


Figure 6*: NPV for the realized path when investments are optimized for either a single path (blue) or a probability distribution of paths (red).*

The blue bars show the solution value when investments are optimized for a single path, and the red bars show the solution value when the investments are optimized for any of the five probability distributions PD1–PD5. Figure 6 shows that the solution obtained by optimization over probability distributions PD1–PD5 actually seems to be the best solution overall, not least because it is always better than the worst solution obtained by the path-wise optimization. A decision based on a business-as-usual scenario might actually be the worst decision to take.

Obviously quite few different solutions are obtained. This is partly a consequence of the integer requirements on the decision variables, and partly due to the restrictions imposed by the model, including the production increase requirements.

The integer requirements on the decision variables originate to a large extent from simplifications made to avoid nonlinearities in the model, while keeping the number of variables and thus the amount of input data reasonably low. As an example, the evaporation plant could have been designed in a number of different ways. To establish the relation between cost and steam saving for the different designs, simulations and optimizations are needed. Thus, only a few evaporation plant designs are included in the model. To obtain many different solutions, as little as possible of these kinds of pre-optimizations, should be carried out.

The solution obtained when optimizing under uncertainty (using probability distributions PD1–PD5) is exactly the same as the solution obtained when optimizing for any of the scenarios M2, S1, or S2. One explanation for this is that the energy market parameters changes with time within the scenarios (which they do also for BAU and M1, but in those scenarios the change is smaller and comes later). Although these variations in the energy market parameters within scenarios are not actual uncertainties (they appear also when the probability is set to 100% for one scenario), they also, like the stochastic optimization, promote flexible solutions which are robust to changes in the energy market conditions. Moreover, a more pronounced difference, for example between the electricity prices in different scenario building blocks, would lead to bigger differences in optimal solutions.

5.3.2 Sensitivity to probability distribution variations

The results presented above and in Paper II show that the probability distribution can be changed within reasonable limits without changing the optimal solution. In Paper III this analysis was taken one step further by seeking to find just how much the probability distribution could be varied without altering the optimal solution.

The analysis was carried out by increasing the probability for one scenario while the probabilities for the others were decreased and kept equal, until the breakpoint where the optimal solution switched from ‘Just enough lignin’ (see Figure 5) to another solution. The breakpoint probabilities are shown in Table 4.

Table 4: *Breakpoint probabilities for the scenarios. See Figure 5 for reference to optimal solution alternatives.*

Scenario	Breakpoint	Change of optimal solution
BAU	80%	Just enough lignin → RBU + turbines
M2	100%	*no change*
S2	85%	Just enough lignin → S2 solution[7]
M1	99%	Just enough lignin → RBU + turbines
S1	100%	*no change*
E	42%	Just enough lignin → S2 solution[7]
E	51%	S2 solution[7]→ Max lignin

[7] The ‘S2 solution’ refers to a variation of the ‘Just enough lignin’ solution, presented with numbers in brackets in Figure 5.

The probability for the scenario BAU can be up to 80% before the solution switches. For the scenarios S2 and M1 the breakpoint is even higher, and for the scenarios M2 and S1 it is 100%, which means that there is no switch. So far, the 'Just enough lignin' solution seems to be robust.

The breakpoint probabilities for scenario E are substantially lower than those for the other scenarios. Although a breakpoint probability of 42% might seem low, the extreme properties of this scenario make it unlikely that its probability will be assumed to be higher. The levels of the breakpoint probabilities thus indicate that the optimal solution under uncertainty is robust to changes in the probability distribution.

5.3.3 Strategic or short-term perspective

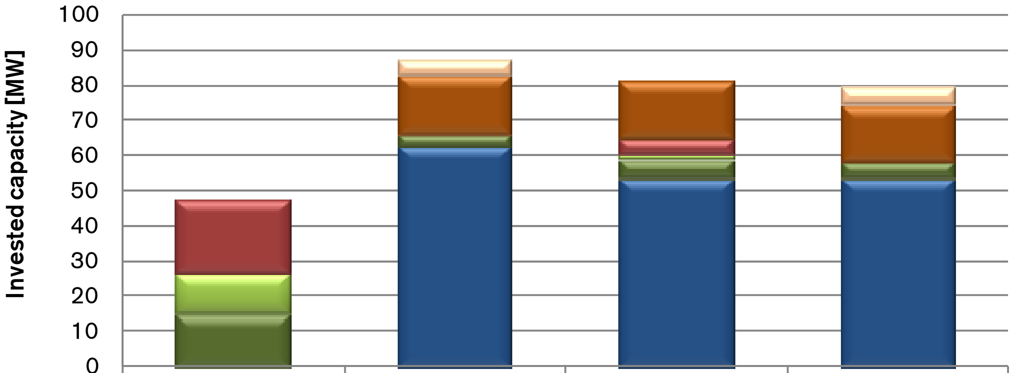
The economic lifetime and the discount rate can be changed in order to reflect either a more short-term or a more strategic perspective on investments (see Section 5.2.2). As shown in Paper II, the resulting annuity factor is the critical parameter in this case study.

Figure 7 shows that a new solution is obtained for the short-term view optimizations which did not arise in the base case optimizations (compare to Figure 5). This solution is, however, very similar to the 'Just enough lignin' solution which is optimal for probability distributions PD1–PD5 when the annuity factor is 0.1. The similar 'Short-term' solution is, correspondingly, optimal for all probability distributions and all the single paths when the annuity factor is 0.2.

When the annuity factor is 0.2, only two different solutions are obtained. These two differ only in the investment in district heating from 60°C heat, and they yield almost exactly the same NPV. The variations are larger when the annuity factor is 0.1 since differences in future price levels have a stronger influence on strategic decisions. The results thus confirm that, with a more strategic view on investments, it becomes more important to account for uncertainties when evaluating investments.

5.3.4 Timing of investments

The proposed modelling approach enables the timing of investments to be studied. The results presented so far, however, only include solutions where investments are made at the root node of the scenario tree. In Paper III we studied the case when the production increase is assumed to be planned for year 2020 instead of year 2010, in order to obtain a solution with investments at multiple stages.



	RBU + turbines	Max lignin	Just enough lignin	Short-term
DH from 60°C heat	0	4.6	0 (0)	4.6 (0)
DH from 100°C heat	0	16.3	16.3 (16.3)	16.3 (16.3)
DH from LP steam	20.9	0	4.6 (4.6)	0 (0)
Condensing turbine	11.4	0	1.4 (0.9)	0 (0)
Back-pressure turbine	15.1	3.8	5.3 (4.8)	4.7 (4.7)
Lignin separation plant	0	62.4	53.6 (56.6)	53.6 (53.6)
annuity factor, a=0.1 Optimal solution for:	BAU, M1	E	PD1–PD5, M2, S1, S2[8]	
annuity factor, a=0.2 Optimal solution for:				PD1–PD5, M2, S1, S2, E, (BAU, M1)

Figure 7: *Optimal solution dependence on the annuity factor.*

An optimal solution is now obtained which involves investments in years 2010 and 2020. The initial investments are made in electricity production and district heating. To meet the requirements on an increased production, additional investments in a lignin separation plant are made 10 years later. With the changed assumptions about the timing of the production increase, we end up with an optimal solution for which the decisions made at later stages depend on the energy market conditions and therefore vary slightly between the scenarios.

5.4 Conclusions of the case study

The methodology proposed in this thesis enables the identification of an investment plan for process integration measures that will be beneficial for a variety of scenarios. This solution – the investment plan – is the best overall solution, compared to the solutions obtained by a traditional sensitivity analysis.

[8] The optimal solution for the scenario S2 when T = 30 years and r = 9% (resulting in an annuity factor of 0.1) is given by the numbers in brackets. For T = 15 years and r = 6% (resulting in the same annuity factor), the optimal solution is given by the 'Just enough lignin' solution.

One of the worst decisions to take is the one based entirely on a business-as-usual scenario. It is shown that uncertainties in future energy market conditions are most important to consider if a long-term perspective on investments is employed.

Furthermore, the identified solution is robust in the sense that the probability distribution (which can be very difficult to estimate) can be changed within reasonable limits without changing the optimal solution.

In this case study, the optimal solution could have been obtained through a sensitivity analysis. In other words, some of the solutions obtained from optimizations with 100% probability for one of the scenarios are equivalent to the solution from the optimization under uncertainty. We know this, however, only because we carried out the stochastic optimization. Using this methodology, we will always find the solutions obtained in a sensitivity analysis – if any of these are optimal – but in addition we also have the possibility of finding solutions that are not optimal for any single scenario, but yield a high NPV for all of them.

The computation time needed to find the optimal solution was about one minute, which should be considered quite fast, implying that with refinements of the model the computation times would probably still be reasonable.

The results imply that there are quite few solutions to the optimization model, which is partly a consequence of the integer requirements on the decision variables and the restrictions imposed by the model. The integer requirements originate from simplifications made in the extraction of input data in order to avoid using nonlinear functions in the mathematical model. Although needed in many cases, as little as possible of these kinds of pre-optimizations should be carried out. A more pronounced difference between the scenario building blocks would also lead to bigger variations in optimal solutions obtained.

6 Conclusions

It has been shown that it is possible to adopt a systematic approach for the optimization of investments in process integration under energy price and policy uncertainty. A methodology has been proposed, and a case study has been carried out that illustrates its use. It has been shown that by basing the methodology on a combination of methods and tools from process integration and stochastic programming, a better understanding of the robustness of investment decisions in process integration can be attained.

The optimization approach enables the identification of the process integration investments that will yield the highest expected net present value. The model is formulated such that uncertainties of future energy market conditions are explicitly considered. The proposed methodology also provides a way to study the timing of investments in a multistage stochastic programming approach. It has been found that an important aspect of the methodology is the modelling of scenarios as development paths.

Uncertainties are modelled in a scenario-based approach, and probabilities for the different scenarios have to be estimated. In a case study we found, however, that the probability distribution could be varied substantially without altering the optimal solution (see Section 5.3.2). It is not unlikely that this might be the case also in other applied studies, and even if it is not, it should be easier to assume a probability distribution than to determine which scenario will be the true future outcome. Moreover, for a case when the optimal solution is altering, the decision-maker would get the opportunity to choose between these alternatives if using the methodology developed.

It has been shown that the proposed approach enables the optimization of combinations of measures for which the outcome is directly and indirectly affected by the implementation of the other measures, as well as by uncertain market conditions. In order to make the most benefit of this property, it is important to avoid a too extensive pre-optimization.

In addition to the general conclusions presented here, a number of conclusions are drawn specifically for the case study. These are presented and discussed in Section 5.4. An important finding is that the computation times are quite modest (about one minute), which means that refinements can be made, for example in the scenario model, while probably still having reasonable computation times.

7 Further Work

The results from the case study as well as the experience from the work of developing the methodology suggest that further work should focus on the modelling of uncertainties. This chapter presents some opportunities for improvement of the proposed methodology. Application of the methodology to real cases is also necessary to find out more about where further development is needed.

7.1 The scenario model

A number of aspects of the scenario model would benefit from further development. In this section, a few such opportunities for improvement will be discussed.

The scenario building blocks used in this thesis are generated using a tool for creating energy market scenarios for year 2020. The development paths built from these blocks are in this thesis, however, assumed to range from 2010 to 2040. The modelling of scenarios as development paths has been shown to be an important aspect of the methodology, and should therefore be modelled more carefully.

It would therefore be an important improvement to have time as input for the generation of scenario building blocks. It should be possible to give as input for which year the scenario building block shall be valid in order to enable differences between blocks for the near and the distant future. An example is that carbon capture and storage is not yet available to such an extent that coal power plants with CCS can be assumed to be the marginal electricity producer, but in the future this might be possible. Another time-dependent property for Swedish conditions is whether electricity price is assumed to be set on a common Nordic electricity market or a North European.

The results of the case study also showed that the difference between scenario blocks was modest for some parameters, especially the electricity price. It would probably be an improvement to include more diversified scenario building blocks. These can possibly be included in scenarios with low probabilities if they are very different from the main building blocks. All building blocks should, however, still be realistic. One way to obtain realistic data with more variation is to consider more of the input parameters to be uncertain with varying values – for example, green electricity certificates, green transportation fuel certificates, or fossil fuel prices. In the scenario model used in this thesis, electricity certificates are assumed to follow the CO_2 emissions charge, transportation fuel certificates are not considered at all, and fossil fuel prices are assumed constant.

7.2 Uncertainty regarding operating availability

The scenario model should be developed to enable the study of other kinds of uncertainties. The most important barriers to energy efficiency in Swedish pulp and paper industry are technical risks such as the risk of production disruptions and costs related to these risks (Thollander and Ottosson, 2008). 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 regarding the operating availability. The operating availability would therefore be an interesting parameter to vary in further studies.

Operating availability is a parameter whose uncertainty is not correlated with the uncertainties in energy market parameters, which implies that a new framework for scenarios has to be developed to model this kind of uncertainty.

7.3 Trade-off between profitability and CO_2 emissions reductions

The model can, with small adjustments, be used to study the trade-off between the net present value and the CO_2 emissions reductions for investments in improved energy efficiency. This work has begun (Svensson and Berntsson, 2008), but will continue with further developments of the methodology.

7.4 Applied studies

So far, the methodology developed has been applied to a case study of a model mill. Although it is called a case study, it is theoretical and far from a real case applied to a real plant. In order to learn where the methodology needs most improvement it is important to carry out such a real case study in cooperation with decision-makers at a real industrial plant.

8 Nomenclature and Abbreviations

a	annuity factor
AC	annualized yearly cost of an investment (see Appendix)
C_t	net cash flow in year t
ℓ	level, or time stage, of the scenario tree
M_{LIG}	parameter with sufficiently high value in a so-called *big-M* constraint, see Constraint (5), p. 25.
n	a node of the scenario tree
$p(n)$	the parent of a node n in the scenario tree
p_s	the probability for scenario s to occur
r	discount rate
RVF	the residual value of an investment as a fraction of the investment cost (see Appendix)
RV_T	the residual value of an investment in year T (see Appendix)
s	scenario, development path
S	set of all scenarios s
t	time measured in years
T	economic lifetime, calculation horizon, measured in years
x	vector of all decision variables in the optimization model
x_0	vector of all decision variables associated with the initial investment
x_s	vector of all decision variables corresponding to scenario s
x_m^n	binary variable that equals 1 if measure m has been implemented before node n, and is 0 otherwise
$\hat{x}_m^n$	binary variable that equals 1 in node n if an investment in measure m is made in node n and is 0 otherwise

Greek symbols

α_{LIG}^n	lignin extraction rate in node n
λ^n	existing lignin extraction capacity for the evaporation plant in node n
$\hat{\lambda}^n$	added lignin extraction capacity for the evaporation plant in node n
ξ^n	vector of uncertainty parameters for node n (notation used in Paper III)
ω_s	vector of uncertainty parameters for scenario s (notation used in Papers I and II)

Scenario notation

BAU	Business-as-usual – minor attention to climate issues
M1	Moderate climate concern – distant future
M2	Moderate climate concern – near future
S1	Sustainability – distant future
S2	Sustainability – near future
E	Extremely rapid change towards sustainability
PD1–PD5	Probability distributions for the scenarios

Abbreviations

BAU	Business As Usual
CCS	Carbon Capture and Storage (or Carbon Capture and Sequestration)
CHP	Combined Heat and Power
DH	District Heating
E[]	Expectation, Expected value
FRAM	Future Resource-Adapted pulp Mill
HWWS	Hot and Warm Water System
IEA	International Energy Agency
LP	Low Pressure (steam)
MILP	Mixed-Integer Linear Programming
NPV	Net Present Value
PD	Probability Distribution
PIvap	Process Integrated eVAPoration plant
RBU	Recovery Boiler Upgrade

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Acknowledgements

Questions and answers, those are what research is all about. The last question to answer in this thesis is why I started it all, or better: why I continued. The answer is of course that there is a number of people who have encouraged and supported me in different ways, and I will take this opportunity to thank some of them.

First, I would like to thank my main supervisor, Thore Berntsson, for believing in me enough to provide me with the opportunity to work on this project and for continued encouragement by being the visionary optimist I sometimes fail to be myself.

I would also like to thank my co-supervisor, Ann-Brith Strömberg, for valuable comments and corrections to my optimization model and to my reports and articles, always asking one more difficult question leading me to learn more. Thanks also to Michael Patriksson for feedback on the papers, and for help in setting up the cooperation between “energy experts” and “optimization experts”.

The Swedish Energy Agency is gratefully acknowledged for financial support.

At work at VoM many people crossed (or are still crossing) my way. A big “thank you” to all of you, PhD students, seniors and others, for the great VoM atmosphere we all know and appreciate. I would especially like to thank Erik Axelsson, Marcus Olsson, and Johanna Jönsson, who not only have provided me with input to my case studies, but also have taken the time to explain and discuss their assumptions, calculations, and results with me. Thanks to my former office-mate Catherine Laaksometsä for welcoming me to “her” office, being my guide to everything that was new when I started working at VoM. Thanks also to Rickard Fornell who shares the office with me today, always patient when I get tired of working and start talking – or rather babbling.

Finally, I would like to thank my parents for bringing me up to be curious about how the world works, for asking questions and debating answers about mathematics, the future of our planet, life in space, or whatever was the topic of that day's breakfast or dinner conversation. Thanks to you and to my sisters for loving me and always being proud of me.

Although I am, of course, proud to have completed this thesis, it is not nearly the most important thing I did this year. The last thank you goes to Hans for making me believe that I could do anything I want. Now that you have your PhD degree, I really have to get mine. Who wants to be second best? Thank you for always loving and supporting me.

Appendix:
Residual value calculations

The residual value of investments was discussed in Section 3.3.3. The details of the calculations for the approach used in this thesis are presented in this appendix. The idea is to choose the residual value such that it exactly cancels out the annualized investment cost for the remaining years of the investment lifetime. Using the notation from Section 3.3.2, the annualized yearly cost AC of an investment C_t made in year t and with an economic lifetime T is given by

$$AC = C_t \frac{r}{1-(1+r)^{-T}}. \tag{A1}$$

If the investment is made in year t, the lifetime of the investment ends at year $t + T$. The calculation horizon ends at year T. The residual value RV_T of the investment in year T is then calculated as the value of the annualized costs between year T and year $t + T$ discounted to year T according to the following expression.

$$RV_T = AC \frac{1-(1+r)^{-t}}{r} = C_t \frac{1-(1+r)^{-t}}{1-(1+r)^{-T}}. \tag{A2}$$

If the residual value is discounted to the time the investment is made, year t, it can be expressed as a fraction RVF of the investment cost as

$$RVF = \frac{RV_T}{C_t}(1+r)^{-(T-t)} = \frac{(1+r)^t - 1}{(1+r)^T - 1}. \tag{A3}$$