Economy and CO_2 emissions trade-off: A systematic approach for optimizing investments in process integration measures under uncertainty

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Abstract

In this paper we present a systematic approach for taking into account the resulting CO_2 emissions reductions from investments in process integration measures in industry when optimizing those investments under economic uncertainty. The fact that many of the uncertainties affecting investment decisions are related to future CO_2 emissions targets and policies implies that a method for optimizing not only economic criteria, but also greenhouse gas reductions, will provide better information to base the decisions on, and possibly also result in a more robust solution. In the proposed approach we apply a model for optimization of decisions on energy efficiency investments under uncertainty and regard the decision problem as a multiobjective programming problem. The method is applied to a case of energy efficiency investments at a chemical pulp mill. The case study is used to illustrate that the proposed method provides a good framework for decision-making about energy efficiency measures when considerations regarding greenhouse gas reductions influence the decisions. We show that by setting up the problem as a multiobjective programming model and at the same time incorporating uncertainties, the trade-off between economic and environmental criteria is clearly illustrated.

Keywords: process integration, CO_2 emissions reductions, optimization under uncertainty, multiobjective optimization.

1. Introduction

Investment decisions in industry are often based on a number of conflicting objectives, although economy is usually the main focus. For investments in energy efficiency, the increased climate concern in society makes, however, the CO_2 emissions associated with industrial investments a more important issue. For strategic investments especially, economy and emissions reductions depend on the future energy market. Electricity and fuel prices, marginal electricity production and marginal biofuel usage, and emissions charges and taxes are all examples of energy market parameters that are highly uncertain, but directly influence the profitability and the CO_2-reducing potential of the investments. Both the multiobjective character and the uncertainty of the parameters make decision-making in industry a complex task.

The aim of this paper is to present a systematic approach for analyzing the trade-off between economy and CO_2 emissions when investments are optimized under uncertainty. A methodology for identifying robust investments in energy efficiency under uncertainty, which was presented and illustrated in previous papers (Svensson et al., 2008a; 2008b; 2008c), is once again applied in a case study. Here, the purpose is to illustrate how the methodology can be extended to include both an economic and an environmental objective. Many of the uncertainties affecting investment decisions are related to future CO_2 emissions targets and policies, which implies that a method for optimizing both economic and environmental criteria will provide better information to base the decisions on, and possibly also result in a more robust solution.

A computer model of a chemical pulp mill faced with a production increase will serve as an example to demonstrate the use of the proposed approach. The model of the mill is the same one as was used in Svensson et al. (2008c). The pulp and paper industry is the fourth largest industrial energy user in the world (IEA, 2007), which makes it important in the progress to mitigate climate change.

Most strategies for improvement of the energy efficiency of an industrial plant will lead to reductions of CO_2 emissions if a wide systems perspective is employed. For example, by reducing the use of fossil fuels, the emissions are directly decreased on-site. Biomass is generally assumed to be CO_2-neutral; nevertheless, the reduction of biofuel use will also lead to CO_2 emissions reductions, but in this case off-site. This is because reduced usage at one plant enables the substitution of fossil fuels elsewhere, thereby reducing overall emissions. Also decreased imports or increased exports of electricity will affect the net CO_2 emissions.

Cost-effective energy savings and potential CO_2 reductions have been identified in the pulp and paper sector in several studies (Axelsson and Berntsson, 2008; Martin et al., 2000; Möllersten et al., 2003). The cost of CO_2 reduction is, however, dependent on, for example, the electricity prices and the marginal electricity production, which are uncertain parameters. Furthermore, the trade-off between cost-effectiveness and CO_2 reductions is unclear. By applying the methodology proposed by Svensson et al. (2008b), the uncertainties are directly incorporated in the optimization, and the trade-off between CO_2 reductions and profitability can easily be analyzed.

2. Related work

The benefits of applying multiobjective optimization in process integration studies have been illustrated in a number of papers. For example, the use of multiobjective optimization for the optimization of an integrated steel plant has been found to increase the knowledge of the trade-off between different objectives, but also of the system characteristics (Sandberg and Larsson, 2004). One methodology for process integration is pinch analysis (Kemp, 2007; Smith, 1995). A multiobjective approach in combination with pinch analysis has been used for the thermo-economic optimization of synthetic natural gas production from wood (Gassner and Maréchal, 2008) and for the trade-off between energy costs and capital costs in site-wide applications (Klemeš et al., 1997). The Multi Objective Pinch Analysis (MOPA) was developed, as an extension to traditional pinch technology, to include several targets, energy, wastewater, and volatile organic materials (Geldermann et al., 2006). Methodologies for pollution prevention based on process integration have been developed to incorporate the multiobjective optimization of process economic and environmental performance (Gao et al., 2005). There are also process integration studies where a number of conflicting criteria such as investment costs, fuel consumption, safety, and water recovery are taken into account (Cziner et al., 2005).

There are also other energy-related studies with industrial applications where a multiobjective approach has been applied for the optimization of economic and environmental criteria (see e.g. Li et al., 2006; Tsay, 2002). A number of studies applying a multiobjective approach concern the efficient and sustainable use of energy in industry, but are aimed at the whole industrial sector in a specific region (see e.g. Mavrotas et al., 2007; Soloveitchik et al., 2002).

Heinrich et al. (2007) combined multiobjective and stochastic optimization in a model for policy-making in the electricity supply industry under demand growth uncertainty. The multiobjective approach applied to a stochastic optimization problem is similar to what is done in our study. The applications and the sources of uncertainty are, however, rather different. In our study, the investment options concern energy efficiency in process industry and the methodology is aimed for decision-makers at specific industrial plants, faced with uncertainties in future energy prices and policies.

Finally, there are several recent studies that show the importance of incorporating uncertainties into the optimization of energy investments. (Blyth et al., 2007; Fuss et al., 2008; Laurikka, 2006; Wickart and Madlener, 2007; Yang et al., 2007). The reader is referred to a previous article by the authors of this paper for a more detailed survey of the related work in this area (Svensson et al., 2008b).

3. Methodology

This study has been conducted using a methodology for optimization of investments in energy efficiency under uncertainty (Svensson et al., 2008b). The proposed methodology enables the optimization of investments with respect to their net present value and with respect to their corresponding CO_2 emissions reductions. Uncertainties regarding the future energy market, such as uncertain energy prices or marginal electricity production, are explicitly incorporated in a model for optimization under uncertainty (a stochastic programming model).

Investment decisions in industry are in many cases, as in the case study presented here, essentially based on an engineering design problem. Such problems typically involve simulations, experimental data, and catalogue selections to establish the relationship between design variables and the dependent characteristics and attributes of the design. There is no simple way to model these relations as continuous analytical functions. Instead, the decision variables are typically binary, expressing a choice between discrete options. The necessary simulations and acquiring of data needed for those options can then be made in advance and given as input to the optimization model. Furthermore, the final optimization model is desired to be linear, which will make it easier to solve the model.

Multiobjective optimization deals with optimization models where there are, as in this study, more than one objective. Following next, the two objectives – the economic objective and the CO_2 emissions reductions objective – will be described. After that, the theory of multiobjective optimization will be explained briefly. A paper presenting a more detailed description of the optimization model for the single-objective case, including all constraints, is under preparation (Svensson et al., 2008a).

The general assumptions, which apply to both the economic optimization and the emissions reductions, are that decisions are made 'here-and-now', before uncertainties are resolved and any price changes or energy market changes occur. Uncertain parameters, such as energy prices and policies, and CO_2 emissions from marginal use of biomass or electricity, are modelled using a scenario-based approach.

3.1 The economic objective

The economic objective is to find the combination of investments resulting in the highest expected net present value (NPV). The objective is thus:

$$\max_{\mathbf{x}\in\Omega} f_{\mathrm{NPV}}(\mathbf{x}) := -C_0(\mathbf{x}_0) + \sum_{s\in S} p_s \sum_{t=1}^{T} \frac{C_t(\mathbf{x}_0, \mathbf{x}_s, \boldsymbol{\omega}_s)}{(1+r_C)^t}, \tag{1}$$

where

S = set of all scenarios s,
p_s = probability for scenario s to occur,
$\boldsymbol{\omega}_s$ = uncertain price parameters for scenario s,

Ω = solution space, i.e. the set of all feasible solutions $\mathbf{x}$,
$\mathbf{x} = (\mathbf{x}_0, \mathbf{x}_s)$ = all decision variables, representing e.g. investment and operating decisions,
$\mathbf{x}_0$ = decision variables associated with the initial investment (not dependent on s),
$\mathbf{x}_s$ = decision variables corresponding to scenario s,
$C_0(\mathbf{x}_0)$ = initial investment cost function,
$C_t(\mathbf{x}_0, \mathbf{x}_s, \boldsymbol{\omega}_s)$ = function for the net cash flow (revenues minus costs) in year t,
T = economic lifetime (in years) of investments,
r_C = discount rate used for cash flows.

The initial investment, C_0, is required to be the same for all scenarios since the first investment decision is taken before the outcome of the uncertain parameters is known. The net cash flow of the final year, C_T, is adjusted for the value remaining after the economic lifetime (the residual value).

3.2 The CO_2 objective

The CO_2 objective is to maximize the expected net CO_2 emissions reductions. Using the same notation as for the economic objective, the CO_2 objective is expressed by:

$$\max_{\mathbf{x}\in\Omega} f_{CO2}(\mathbf{x}) := \sum_{s\in S} p_s \sum_{t=1}^{T} \frac{E_t(\mathbf{x}_0, \mathbf{x}_s, \boldsymbol{\pi}_s)}{(1+r_E)^t}, \tag{2}$$

where

$\boldsymbol{\pi}_s$ = uncertain CO_2 emissions parameters for scenario s,
$E_t(\mathbf{x}_0, \mathbf{x}_s, \boldsymbol{\pi}_s)$ = function for the net CO_2 emissions reductions in year t,
r_E = discount rate used for CO_2 emissions.

Discounting of CO_2 emissions is not conventional; neither is it necessary in traditional CO_2 emissions calculations. Here, however, the multiobjective problem formulation, in combination with the assumption that investments can be made at different points in time, makes some kind of discounting essential. Tests have shown that by choosing $r_E = 0$, corresponding to no discounting, the multiobjective optimization will give some meaningless results. This can be understood by the following line of reasoning. Consider first the fact that cash flows are always discounted. Then, with no discounting for emissions, a simple way of improving the CO_2 emissions objective with only a slight decrease in net present value is to make the investments in CO_2 reductions as late as possible. The cost will then be low in present value, but the reductions count equally as if they were carried out today. In the long run, such a view would imply that it is always better to postpone the investments in CO_2 reductions. This would mean that it is always better to primarily earn money now, and save the climate later.

Because discounting of emissions is unconventional, both discounting and no discounting are possible model settings through the choice of an appropriate value for r_E. The recommendation should, however, be to apply emissions discounting. Such a choice will be in agreement with the political intention and calls for reductions in CO_2 emissions already today. If emissions reductions are achieved today, the accumulated reduction of CO_2 in the atmosphere will be substantially larger in the future than if the emissions reductions are achieved 30 years from now.

It is not easy to know what would be an appropriate value of the emissions discount rate, but it seems natural to choose the same value as for the cash flow discount rate. If the emissions discount rate, r_E, is chosen to equal the value of the cash flow discount rate, r_C, the time preference which was discussed above will be cancelled out.

3.3 Multiobjective optimization

The two objectives presented above are both conflicting and incommensurable, as is often the case when there is more than one objective. This makes it natural to formulate the investment decision problem as a multiobjective optimization model. Through this approach, the trade-offs can more easily be made visible.

A survey of different methods for multiobjective optimization in engineering design problems, including basic theory and definitions used in the subject, can be found in Andersson (2000). For a more comprehensive overview of the multicriteria optimization literature, the reader is referred to Ehrgott and Gandibleux (2002). Here the basics will be presented as a base for further discussions on the choice of an appropriate method in this case study.

The multiobjective optimization problem is expressed by:

$$\max_{\mathbf{x}\in\Omega} \mathbf{F}(\mathbf{x}) := \left(f_{\mathrm{NPV}}(\mathbf{x}), f_{\mathrm{CO2}}(\mathbf{x})\right) \tag{3}$$

Mathematically, the maximization of $\mathbf{F}(\mathbf{x})$ is not clearly defined. There is, however, a set of solutions called Pareto-optimal solutions, from which any final solution should preferably be chosen. The Pareto-optimal solutions are also known as non-dominated solutions, which means that no solutions exist which are better for all objectives. In other words, for the Pareto-optimal solutions, the improvement of one objective is always obtained at the expense of at least one of the other objectives. A solution which is not in the Pareto-optimal set would not be a rational choice since it can be improved without degradation of any objective. The trade-off between different objectives can be visualized in a graph showing the Pareto front (see Figure 1). The term ‘Pareto front’ refers to the domain of objective function vectors of Pareto-optimal solutions.

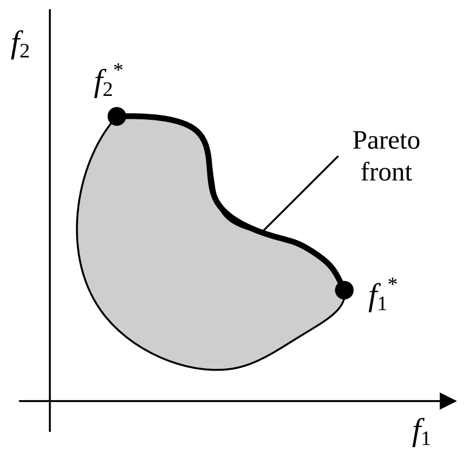

Figure 1: Objective function space for a two-objective optimization problem.

3.3.1 The weighted-sum approach and the ε-constraint method

The multiobjective optimization can be solved using a variety of different methods. The model developed for this study enables the use of two different methods, the weighted-sum approach and the ε-constraint method. The weighted-sum approach is easy to use; the objective is formulated as a weighted sum of the different objective functions. The optimization problem (3) is reformulated as (4) according to the weighted-sum approach.

$$\left.\begin{array}{l}\max\limits_{\mathbf{x}\in\Omega} \lambda_1 f_{\mathrm{NPV}}(\mathbf{x})+\lambda_2 f_{\mathrm{CO2}}(\mathbf{x}) \\ \text{subject to } \lambda_1,\lambda_2>0,\ \lambda_1+\lambda_2=1\end{array}\right\} \tag{4}$$

The preference of the decision-maker is taken into account by the choice of the weights, λ_1 and λ_2. There are, however, some drawbacks with this method. First, it may be necessary to normalize the objective functions, because they are in many cases incommensurable and of different magnitudes. Also, it might be difficult to determine the weights, since it is not clear how they affect the solution, and it might be hard to achieve an even spread of solutions on the Pareto front. Furthermore, for optimization models containing integer variables, as is the case for the model in this study, it is not always possible to find all solutions in the Pareto-optimal set (see e.g. Klamroth et al., 2004). The same is true for non-convex function sets in general, for example the one in Figure 1.

The above-mentioned drawbacks of the weighted-sum approach are avoided in the ε-constraint method. In that method, only one of the objective functions is optimized; the others are reformulated as constraints. For optimization problem (3), either $f_{\mathrm{NPV}}(\mathbf{x})$ or $f_{\mathrm{CO2}}(\mathbf{x})$ can be selected for optimization. If $f_{\mathrm{NPV}}(\mathbf{x})$ is selected, the reformulation according to the ε-constraint method is given by:

$$\left.\begin{array}{ll}\max & f_{\mathrm{NPV}}(\mathbf{x}) \\ \text{subject to} & f_{\mathrm{CO2}}(\mathbf{x})\geq\varepsilon \\ & \mathbf{x}\in\Omega\end{array}\right\} \tag{5}$$

Here, the preference of the decision-maker is articulated by different choices of the constraint value ε. Unlike the weights of the weighted-sum approach, the constraint value ε has a clearer meaning. Optimization of the two objective functions independently gives two extreme values for ε. The upper limit $f_{\mathrm{CO2}}^*(\mathbf{x})$ is given by the maximum value of $f_{\mathrm{CO2}}(\mathbf{x})$ for $\mathbf{x}$ in Ω. For higher values of ε there are no feasible solutions to (5). The lower limit is given by the value of $f_{\mathrm{CO2}}(\mathbf{x^*})$ where $\mathbf{x^*}$ is the optimal solution to the maximization of $f_{\mathrm{NPV}}(\mathbf{x})$ for $\mathbf{x}$ in Ω. Lower values of ε will not yield any improvement in the optimal objective value for (5). By choosing constraint values ε evenly between the two extremes, an even spread of solutions on the Pareto front can be achieved more easily than by using the weighted-sum approach. The above discussion can be generalized to be valid for more than two objectives.

In this study, we have applied the ε-constraint method, since our objectives are in fact incommensurable and weights would have been difficult to decide on. Furthermore, the model contains integers, which requires the use of the ε-constraint method in order to be sure of finding all Pareto-optimal solutions. The values of ε were chosen to be evenly spread over the range between the upper and lower limits, $f_{\mathrm{CO2}}^*(\mathbf{x})$ and $f_{\mathrm{CO2}}(\mathbf{x^*})$, described above. Because of the integrality of the model it might, however, not be possible to obtain solutions with $f_{\mathrm{CO2}}(\mathbf{x})$ exactly equal to each value of ε.

4. The case study

The optimization model essentially consists of two parts – a model of the pulp mill and an energy market scenario model. The model of the pulp mill used in this study is the same as the one used in previous work by the authors of this paper (Svensson et al., 2008c). The focus then was the economic optimization of energy efficiency investments under uncertainty. Here, the focus is rather on the CO_2 emissions reductions optimization and the trade-off between emissions reductions and the economic objective. The decision variables are the same for both objectives, describing the options for energy efficiency investments, and what the energy savings should be used for. The pulp mill model and the scenario model are described next.

4.1 The pulp mill

The studied mill is a computer model of a typical Scandinavian chemical market pulp mill. It was originally developed for the Swedish national research programme "The Future Resource Adapted Pulp Mill" (FRAM, 2005). The mill is assumed to be faced with a planned production increase of 25%, a case which was studied by Axelsson et al. (2006b).

The production increase will lead to an increase of black liquor flow to the recovery boiler, but also an increased steam demand of the process. The process stream of black liquor comes from the pulp digester and contains a wide range of substances, among others the chemicals used for digesting the pulp, but also lignin, which is a woody by-product in the pulp production process. The purpose of the recovery boiler is to recover the digester chemicals in the black liquor, but also to recover the energy of the lignin and produce high-pressure (HP) steam.

The recovery boiler is, in many cases, one of the bottlenecks in the process. The traditional approach to increase the production in such cases is to upgrade the recovery boiler. Such an investment is substantial, but renders the possibility of increasing the electricity production since more HP steam is produced in the upgraded recovery boiler. An alternative approach, to avoid upgrading the recovery boiler, is to extract lignin from the black liquor before it enters the recovery boiler (Axelsson et al., 2006b). The lignin can then be exported for use as a biofuel, and the load on the recovery boiler is decreased. One consequence of that is, however, that the steam production cannot be increased to cover the increased steam demand of the process. Nevertheless, lignin extraction remains an interesting option if steam savings are carried out to at least the amount corresponding to the increased steam demand.

In addition to the steam savings carried out in order to avoid a recovery boiler upgrade, even further steam savings can be made. This will render an energy surplus at the mill. A number of different options for steam savings can be identified by using process integration techniques and methods such as pinch analysis (Kemp, 2007; Smith, 1995). In addition, the amount of available excess heat can be determined. Axelsson et al. (2006a) has identified the potential for energy savings at the studied mill. An obtained steam surplus enables either a further increase of the lignin extraction or an increase of the electricity production. High- and/or medium-pressure steam can be used to produce electricity in a back-pressure turbine, while low-pressure steam can be used in a condensing turbine.

Low-pressure steam is also available for district heating, for which not only steam, but also excess heat of lower quality, can be used. The potential for external delivery of heat naturally depends on whether there is a district heating system near the mill and what the alternative heat production is in that system. Jönsson et al. (2008) showed a larger potential for profitable excess heat cooperation between mills and energy companies in small district heating systems. Hence, we assume here the presence of a small district heating system nearby, and use the same data for that system as were used in the mentioned study. The data and a description of that system were presented in Svensson et al. (2008d).

For input data and assumptions regarding the mill and the opportunities for energy efficiency, the reader is referred to the previous paper by Svensson et al. (2008c).

4.2 The scenario model

The scenario model is constructed on the basis of five scenario blocks which are described below. Blocks 1A and 1B both correspond to a 'business as usual' parameter set, but block 1A is valid in the near future, and block 1B from year 2015 onward. The parameter sets of blocks 2A and 2B correspond to a moderate increase of the CO_2 emissions charge (or a decrease of the CO_2 emissions cap). Block 2A is assumed to be valid in the near future where CO_2 capture and storage (CCS) has not yet been introduced to a large extent, while block 2B is valid from year 2020 onward, with coal power plants with CCS as the marginal electricity producer. Block 3, finally, corresponds to an even further increase of the CO_2 emissions charge compared to blocks 2A and 2B.

Table 1: Scenario blocks of consistent energy market parameter sets.

Block		Description
1A	The Swedish energy market in the near future.	Prices, taxes, marginal production etc. are based on data from Sweden, the first quarter of 2006.
1B	A 'business as usual' evolution of society.	European market marginal price setting. No increase in CO_2 emissions charges. Replaces block 1A after year 2015.
2A	A 'moderate change' evolution of society. (before 2020)	The CO_2 emissions charge is increased compared to the present value. The green power certificates are assumed to drop in price because of the higher CO_2 charge, which also promotes green electricity production. It is assumed that coal power plants with CO_2 capture and storage (CCS) cannot be the marginal electricity producer in this block, which is assumed to be valid up to year 2020.
2B	A 'moderate change' evolution of society. (after 2020)	Replaces block 2A after year 2020. The CO_2 emissions charge equals that of block 2A, but CCS is assumed to be available for marginal electricity production.
3	A 'sustainable' evolution of society.	The CO_2 emissions charge is further increased compared to block 2A and 2B. The green power certificates are, consequently, further reduced in price.

The parameter sets are generated using a tool for creating energy market scenarios (Axelsson et al., 2007). The inputs are fossil fuel prices, CO_2 emissions charges, green electricity certificates, and possibly green transportation fuel certificates, from which the marginal electricity production, the marginal biofuel use, and the resulting prices of electricity and biofuel are calculated. Since the tool originally was developed to generate energy market scenarios valid after year 2020, the possibility to have coal power plants with CCS as the marginal electricity producer in scenario block 2B had to be manually disabled. The lignin price and district heating price are calculated based on the output from the scenario-generating tool; see Svensson et al. (2008c) for a description of the underlying assumptions regarding the lignin and district heating prices. The resulting data for the scenario building blocks are presented in Table 2.

Table 2: Parameter sets for the five scenario building blocks.

	Scenario block				
Energy market parameters	**1A**	**1B**	**2A**	**2B**	**3**
Electricity price [€/$MWh_{elec.}$]	38.6	57.3	63.0	60.8	61.9
Green electricity certificates [€/$MWh_{elec.}$]	21.7	16.0	10.6	10.6	5.3
Lignin price [€/MWh_{fuel}]	19.5	22.9	26.9	26.9	31.0
District heating price [€/MWh_{heat}]	21.3	25.3	29.5	29.5	33.7
CO_2 emissions from marginal use of electricity [kg/$MWh_{elec.}$]	723[a]	723[a]	723[a]	136[b]	136[b]
CO_2 emissions from marginal use of biofuel [kg/MWh_{fuel}]	329[c]	329[c]	329[c]	329[c]	329[c]

[a] Operating margin: Coal-fired steam turbine plants.
[b] Build margin: Coal power plants with CO_2 capture and storage (CCS).
[c] Marginal use of biofuel: Co-fired in CFB (Continuous Fluidized Bed) plants.

In the above scenario blocks, the build margin for electricity production is always coal-fired power plants, either with or without CCS (CO_2 Capture and Storage). Usually, future market scenarios are based on assumptions of the marginal electricity production being NGCC (Natural Gas Combined Cycle) plants. The reason why NGCC is not included here is that all of the building blocks are generated on the basis of an assumption of high oil prices, and hence also high natural gas prices. Under such conditions, coal with CCS will be more cost-effective than NGCC for producing electricity. It should also be noticed that we only include building blocks where the marginal use of biofuel is co-firing in CFB (Continuous Fluidized Bed) plants. To obtain a scenario block with a different marginal biofuel user, green transportation certificates have to be introduced.

In order to keep the model simple and clear, we chose here not to include developments with low oil prices or developments with green transportation certificates. The uncertainties that are studied are thus only related to the future CO_2 emissions charges. The assumptions for oil prices and green transportation certificates might, of course, be discussed. However, the purpose here is to illustrate how a methodology combining stochastic and multiobjective optimization can be used as a decision-making tool for investment planning of energy efficiency investment. The development of a scenario model, including the choice of which uncertainties are going to be analyzed, has to be worked out in close cooperation with the decision-maker in each new project. This paper presents the methodology for how to analyze the investments given a decision-maker's view on the future development of the energy market. It is, however, important to realize that the assumptions on marginal electricity production and marginal biofuel use will have significant impact on the results.

The five building blocks, 1A/B, 2A/B, and 3, are combined into five different development paths or scenarios. The paths, which were first suggested by Ådahl and Harvey (2007), describe different developments regarding the attention to climate issues for the future. Figure 2 illustrates development paths that range over 30 years, built upon blocks which are assumed to be valid for five years.

The probabilities for each path are of course not known, but can be assumed and easily changed to test different properties of the probability function.

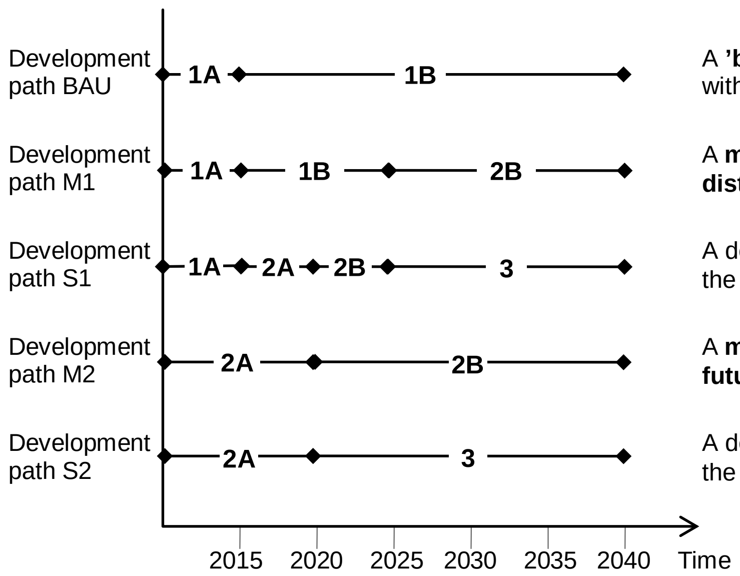

Figure 2: Development paths for energy market parameters.

5. Results and discussion

The results presented in this section are obtained using the ε-constraint method, with the CO_2 objective treated as a constraint. According to the discussion in Section 3.2, the discount rate is set to 9% for both the economic calculations and the CO_2 emissions calculations, and the economic lifetime is assumed to be 30 years. Furthermore, two different probability distributions are used (see Table 3). They are chosen to illustrate the influence of making different assumptions regarding the probabilities for the scenarios. The probability distributions 'A' and 'B' represent two opposing views on the future development of the energy market. The first one has a higher probability for a 'business as usual' development, and the second one has a higher probability for a sustainable development.

Table 3: The two probability distributions used here.

	A	B
BAU	0.30	0.10
M1	0.25	0.15
M2	0.20	0.20
S1	0.15	0.25
S2	0.10	0.30

Investment decisions in industry today are usually based on investment criteria where future prices are not taken into account, and thus implicitly a 'business as usual' development is assumed. There is, however, an awareness of the need for strategic decisions in the presence of uncertain energy prices and policy instruments that the mills are faced with today. Thus, it is reasonable to believe that for decision makers in industry, the view on energy market development can be described by a probability distribution somewhere between distributions 'A' and 'B'.

Both probability distributions 'A' and 'B' result in the same optimal solution when the net present value is maximized. This solution is characterized by lignin being extracted by exactly the amount necessary to avoid upgrading the recovery boiler. The remaining steam surplus is used for increased electricity production. Lower temperature excess heat is used for district heating.

The trade-off between economic and environmental criteria is clearly visualized in a Pareto graph. Figure 3 displays a number of computed points on the Pareto front for each of the two probability functions given in Table 3. The Pareto graph here shows the same kind of characteristics for both cases 'A' and 'B'. As expected, an improvement of the CO_2 objective can be achieved at a lower loss in NPV at a low CO_2 decrease level compared to at a high level. This is because more cost-effective measures for reducing CO_2 emission will be carried out first. For each case study considered, the Pareto curve will make it more clear how an increase of the CO_2 emissions reduction will affect the net present value.

In addition to the trade-off characteristics, Figure 3 illustrates some other interesting results regarding the difference in solution values for the two probability distributions 'A' and 'B'. For distribution 'B', which represents higher probabilities for the sustainability scenarios, it is possible to achieve a higher NPV compared to 'A' for the same CO_2 emission reduction. This is an expected consequence of the higher energy prices in the sustainable development paths.

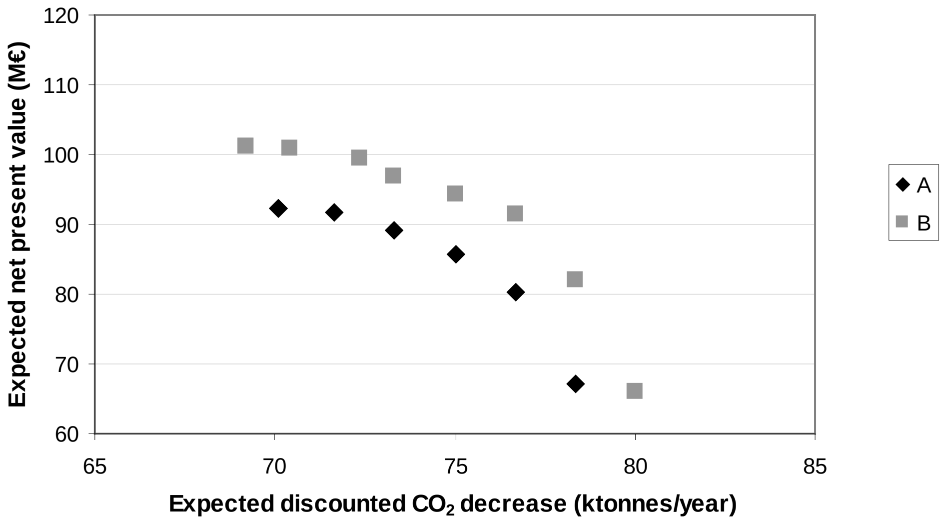

Figure 3: Pareto graph illustrating the trade-off between economic and environmental criteria (NPV and discounted CO_2 emissions) for two probability distributions. Probability distribution 'A' has a high probability for a BAU evolution of society, while 'B' has a high probability for sustainable development paths.

The difference in results for the probability distributions 'A' and 'B' is, however, also due to the different system consequences of making energy efficiency improvements at the mill for the two cases. Consider, for example, the case of an increased electricity production at the mill and notice the difference in marginal electricity production for the different scenario building blocks presented in Table 2. The generated electricity will, in the case of blocks 1A/B and 2A, substitute electricity produced at a coal power plant, yielding substantial reductions in CO_2 emissions. For blocks 2B and 3, on the other hand, the generated electricity will substitute electricity produced at a coal power plant with CCS, yielding less than 20% of the reduction compared to the case with no CCS.

From the discussion above, it becomes clear that there is a need of comparing the CO_2 emissions to some kind of target value, since the maximum achievable reduction varies between different scenarios. Due to the difference in marginal electricity production and marginal biofuel use in the scenarios, the resulting CO_2 reductions will vary between the scenarios even when the same energy efficiency measures are taken. The CO_2 target is here defined as the maximum achievable emissions reductions independently of the cost-effectiveness of the measures, which is given by the solution value to optimization problem (2). Only the energy efficiency measures included in the model are, however, available for determining the target, and hence, measures that already from start have been judged not to be cost-effective are left out of the analysis. The same measures are of course available for all scenarios, and thus the comparison between different scenarios should still be valid.

One way of illustrating the level of reductions compared to the target is shown in Figure 4. Here, we call this kind of graph a target graph. As can be seen, in this case study, the target levels are very similar or even exactly the same for some paths. Paths M2, S1, and S2 have the same target level, which is entirely due to the marginal electricity production and the marginal biofuel use being the same for these paths at each point in time. Also paths BAU and M1 have a similar target level compared to the other paths, which is explained by the fact that the target solution is, for all paths, as will be shown below, characterized by high lignin extraction rates. The CO_2 emissions reductions associated with lignin extraction are equal for all scenario building blocks.

It should, however, although it might seem unnecessary here, be useful to illustrate the results in a target graph, especially if the CO_2 targets are differing more between the scenarios than they are here, or if the probability distributions considered does not yield the same economic optimum. Furthermore, in the case presented here, we now know that the CO_2 emissions reductions can be compared between different paths without any corrections or adaptations to account for differing target levels. The bars denoted by NPV optimum in Figure 4 display the resulting CO_2 emissions decrease for the economically optimal solution under uncertainty. That solution corresponds to the leftmost points in the Pareto graph. The rightmost points are instead corresponding to the target CO_2 emissions decrease.

In this case study, the target graph shows that the economic solution corresponds to a CO_2 emissions reduction that is close to the target. This implies a robustness of the economic solution, since uncertainties in this case primarily are related to uncertainties in the CO_2 emissions charges. This result is connected to the substantial lignin extraction of both the economically optimal solution and the CO_2-optimal solution. In a case where the economic optimum is dominated by electricity production, the difference between the target and the economic optimum would be more significant.

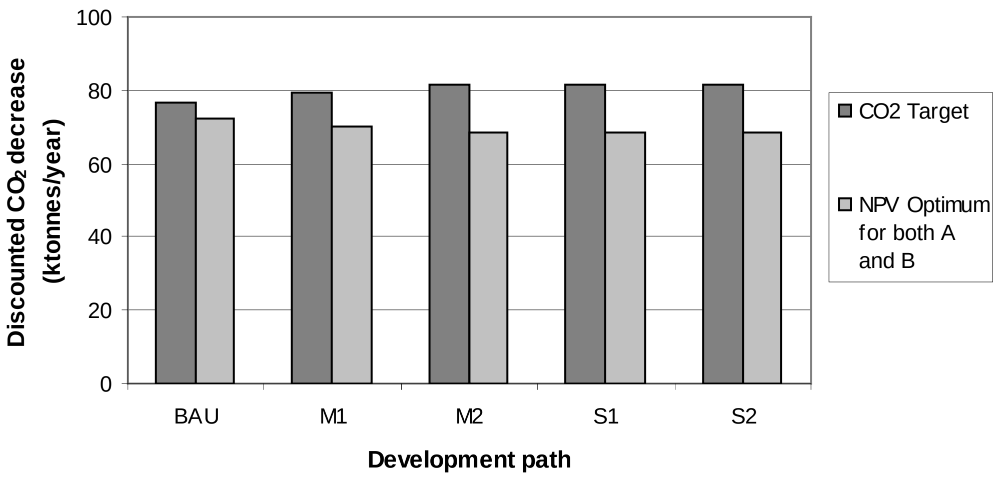

Figure 4: A target graph, where the CO_2 target is the maximum possible CO_2 emission reduction for each path. The NPV optimum is the CO_2 reduction achieved for each path when optimizing the expected value of the NPV. (Only one NPV optimum is displayed here, since both probability distributions 'A' and 'B' yield the same solution.)

The Pareto graph clearly illustrates the trade-off between economy and CO_2 emissions reductions, and a target graph like the one in Figure 4 illustrates the CO_2 reductions compared to a target value. In those graphs, the investments characterizing the different solutions are, however, well hidden. The investments characterizing the different solutions are shown in Figure 5. It can be seen that with an increased demand for CO_2 emissions reductions, one of the first distinct changes is that investments in electricity production are increased. In fact, this corresponds to an increased investment in steam savings to be used for electricity production in the condensing turbine. Eventually, the investments will then shift away from electricity production towards higher lignin extraction capacity.

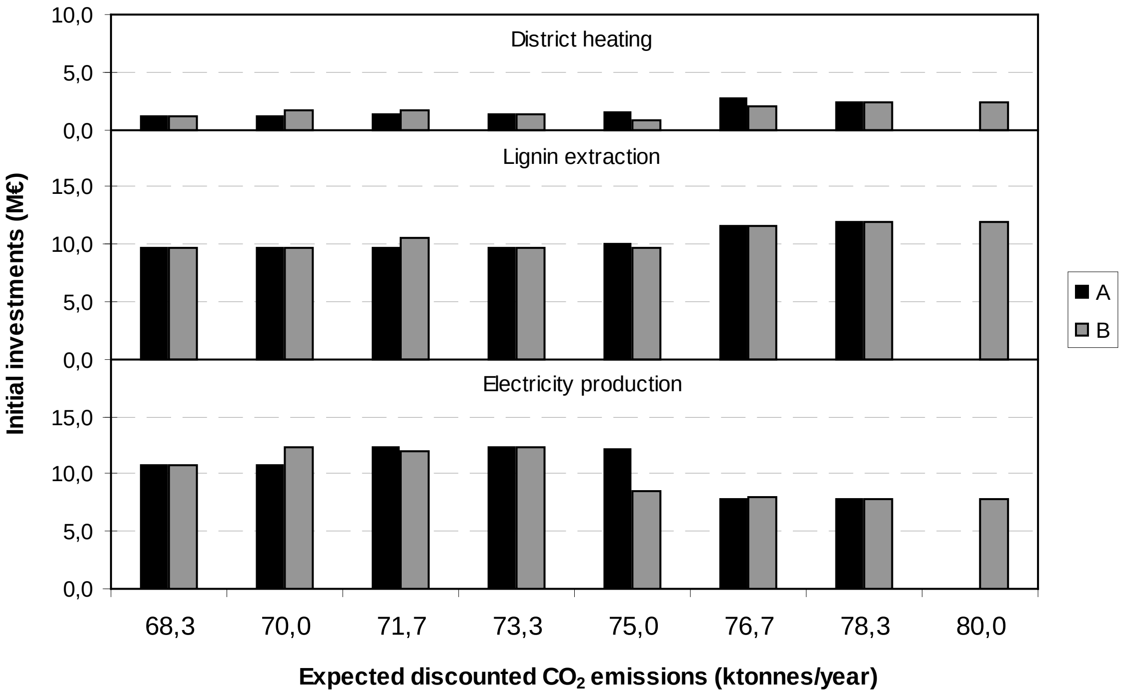

Figure 5: Changes in initial investment (excluding the investments in steam savings) as a function of increasing requirements on the CO_2 emissions reductions. Alternatives A and B refer to the probability distributions in Table 3. The values of CO_2 emissions reductions on the x-axis are the applied ε-values according to the formulation in Eq. (5).

Except for the increase in lignin extraction capacity that occurs at about 75 ktonnes/year of expected discounted CO_2 decrease and the increase in electricity production capacity at about 70 ktonnes/year, Figure 5 shows no distinct changes in initial investments. This implies that the increase in CO_2 emissions reductions are achieved through either a changed allocation of investments within the categories (district heating and electricity production) or through investments that are carried out at a later stage.

A detailed analysis of the investment plan (not only looking at Figure 5) reveals that increased CO_2 emissions reductions are in fact achieved through a combination of later investments in lignin extraction and a shift in both the amount and type of excess heat which is used for district heating. The CO_2 emissions reductions associated with district heating is closely connected to characteristics of the district heating system. The results achieved here would not be applicable for a larger district heating system with other types of heat production. Later investments are primarily carried out in scenarios when faced with a change to building block 3. These investments are mainly made to increase the lignin extraction capacity, but also to increase the heat pump capacity for district heating deliveries. Such investments are, however, not as cost-effective in the other scenario building blocks.

The CO_2 objective is, according to Eq. (2), the expected value of the discounted CO_2 emissions over all future scenarios. This formulation implies that improvement of the objective may be achieved by increasing the CO_2 emissions reduction for one scenario only, keeping the emissions for the other scenarios constant. To avoid this, and ensure that improvements are made for all scenarios, the optimization problem can be reformulated with one CO_2 objective for each path. In the ε-constraint method, all of these objectives are then treated as constraints that can successively be tightened in order to find new Pareto-optimal solutions. An opportunity to adopt this approach is implemented in the model. The number of solutions required to obtain a fairly dense representation of the Pareto front increases, however, exponentially with the number of objectives. Moreover, with more than two objectives, there is no simple way of presenting the Pareto-optimal solutions graphically, but there exists interactive tools for browsing the Pareto front. For example, one such tool is described in Küfer et al. (2003), although for a different type of application.

6. Conclusions

In this paper, we presented a multiobjective approach for the optimization of investments in energy efficiency under energy market uncertainty, based on a previously presented methodology for optimizing such investments under uncertainty (Svensson et al., 2008b). We showed that the proposed approach will increase the knowledge of the trade-off between economic and environmental considerations in the decision-making regarding such investments. Uncertainties can be incorporated in the optimization model also in the multiobjective model formulation.

The multiobjective approach enables the use of Pareto graphs for illustrating the trade-off between the economic and the CO_2 objective. A Pareto graph clearly illustrates the relationship between the two criteria.

We also proposed the use of target graphs, where the CO_2 emissions for one solution are plotted, for each scenario, together with the best possible emissions reductions for that scenario. This kind of graph will provide an aid in the decision-making process, since due to differing marginal electricity production and biofuel use, the CO_2 emissions reductions will vary between the scenarios even when the same energy efficiency measures are taken.

For the case study presented here, the target graph shows that the CO_2 emissions reductions corresponding to an economically optimal solution is quite close to what is maximally achievable. This indicates a robustness of the economic optimum solution, confirming the results of previous work (Svensson et al., 2008c).

Finally, the investments characterizing the Pareto-optimal solutions can be illustrated in graphs showing the initial investment as a function of CO_2 emissions reductions. This kind of graph will provide basic information regarding the investments to roughly explain the characteristics of the Pareto graph. Details about the investment plans can then be achieved through a closer look at the solution data for the interesting solutions.

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References

Andersson, J., 2000. A survey of multiobjective optimization in engineering design, Technical report LiTH-IKP-R-1097. Linköping Institute of Technology, Linköping, Sweden.

Axelsson, E., Olsson, M., Berntsson, T., 2006a. Heat integration opportunities in average Scandinavian kraft pulp mills: Pinch analyses of model mills. Nordic Pulp and Paper Research Journal 21 (4).

Axelsson, E., Olsson, M., Berntsson, T., 2006b. Increased capacity in kraft pulp mills: Lignin separation and reduced steam demand compared with recovery boiler upgrade. Nordic Pulp and Paper Research Journal 21 (4).

Axelsson, E., Harvey, S., Berntsson, T., 2007. A tool for creating energy market scenarios for evaluation of investments in energy intensive industry. In: Mirandola, A., Arnas, Ö., Lazzaretto, A. (Eds.), Proceedings of the 20th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, Padova, Italy, 2007.

Axelsson, E., Berntsson, T., 2008. Profitability and off-site CO_2-emission reduction from energy savings in the pulp and paper industry in different future energy markets. Submitted for publication.

Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., Yang, M., 2007. Investment risks under uncertain climate change policy. Energy Policy 35 (11).

Cziner, K., Tuomaala, M., Hurme, M., 2005. Multicriteria decision making in process integration. Journal of Cleaner Production 13 (5).

Ehrgott, M., Gandibleux, X., 2002. Multiple criteria optimization state of the art annotated bibliographic surveys. Kluwer Academic Publishers, Boston.

FRAM, 2005. FRAM Final report Model mills. STFI, Stockholm, Sweden.

Fuss, S., Szolgayova, J., Obersteiner, M., Gusti, M., 2008. Investment under market and climate policy uncertainty. Applied Energy 85 (8).

Gao, Y., Shi, L., Yao, P.J., 2005. Application of genetic algorithms for process integration and optimization considering environmental factors. Environmental Progress 24 (1).

Gassner, M., Maréchal, F., 2008. Thermo-economic optimisation of the integration of electrolysis in synthetic natural gas production from wood. Energy 33 (2).

Geldermann, J., Treitz, M., Schollenberger, H., Rentz, O., 2006. Evaluation of VOC recovery strategies – Multi Objective Pinch Analysis (MOPA) for the evaluation of VOC recovery strategies. OR Spectrum 28 (1).

Heinrich, G., Howells, M., Basson, L., Petrie, J., 2007. Electricity supply industry modelling for multiple objectives under demand growth uncertainty. Energy 32 (11).

IEA, 2007. Tracking Industrial Energy Efficiency and CO_2 Emissions. OECD/IEA, Paris, France.

Jönsson, J., Svensson, I.-L., Berntsson, T., Mosfegh, B., 2008. Excess heat from kraft pulp mills: Trade-offs between internal and external use in the case of Sweden – Part 2: Results for future energy market scenarios. Submitted for publication.

Kemp, I.C., 2007. Pinch Analysis and Process Integration: A User Guide on Process Integration for the Efficient Use of Energy. Butterworth-Heinemann, Oxford.

Klamroth, K., Tind, J., Zust, S., 2004. Integer Programming Duality in Multiple Objective Programming. Journal of Global Optimization 29 (1).

Klemeš, J., Dhole, V.R., Raissi, K., Perry, S.J., Puigjaner, L., 1997. Targeting and design methodology for reduction of fuel, power and CO_2 on total sites. Applied Thermal Engineering 17 (8-10).

Küfer, K.-H., Scherrer, A., Monz, M., Alonso, F., Trinkaus, H., Bortfeld, T., Thieke, C., 2003. Intensity-modulated radiotherapy – a large scale multi-criteria programming problem. OR Spectrum 25 (2).

Laurikka, H., 2006. Option value of gasification technology within an emissions trading scheme. Energy Policy 34 (18).

Li, H.T., Marechal, F., Burer, M., Favrat, D., 2006. Multi-objective optimization of an advanced combined cycle power plant including CO_2 separation options. Energy 31 (15).

Martin, N., Anglani, N., Einstein, D., Khrushch, M., Worrell, E., Price, L.K., 2000. Opportunities to improve energy efficiency and reduce greenhouse gas emissions in the U.S. pulp and paper industry. Lawrence Berkeley National Laboratory, Berkeley, CA.

Mavrotas, G., Georgopoulou, E., Mirasgedis, S., Sarafidis, Y., Lalas, D., Hontou, V., Gakis, N., 2007. An integrated approach for the selection of Best Available Techniques (BAT) for the industries in the greater Athens area using multi-objective combinatorial optimization. Energy Economics 29 (4).

Möllersten, K., Yan, J., Westermark, M., 2003. Potential and cost-effectiveness of CO_2 reductions through energy measures in Swedish pulp and paper mills. Energy 28 (7).

Sandberg, P., Larsson, M., 2004. Analysing the costs, energy use and environmental performance of an integrated steel plant by applying a multi-objective approach. Paper VI in Larsson, M., 2004. Process Integration in the Steel Industry – Possibilities to Analyse Energy Use and Environmental Impacts for an Integrated Steel Mill. PhD Thesis, Division of Energy Engineering, Department of Applied Physics and Mechanical Engineering, Luleå University of Technology, Sweden.

Smith, R., 1995. Chemical Process Design. McGraw-Hill, Inc, New York.

Soloveitchik, D., Ben-Aderet, N., Grinman, M., Lotov, A., 2002. Multiobjective optimization and marginal pollution abatement cost in the electricity sector – An Israeli case study. European Journal of Operational Research 140 (3).

Svensson, E., Strömberg, A.-B., Patriksson, M., 2008a. A scenario-based stochastic programming model for the optimization of process integration opportunities in a pulp mill. Under preparation.

Svensson, E., Berntsson, T., Strömberg, A.-B., Patriksson, M., 2008b. An optimization methodology for identifying robust process integration investments under uncertainty. Submitted for publication.

Svensson, E., Berntsson, T., Strömberg, A.-B., 2008c. Benefits of using an optimization methodology for identifying robust process integration investments under uncertainty – A pulp mill example. Submitted for publication.

Svensson, I.-L., Jönsson, J., Berntsson, T., Mosfegh, B., 2008d. Excess heat from kraft pulp mills: Trade-offs between internal and external use in the case of Sweden – Part 1: Methodology. Submitted for publication.

Tsay, M.T., 2002. The operation strategy of cogeneration systems using a multi-objective approach. IEEE/PES Transmission and Distribution Conference and Exhibition 2002: Asia Pacific, Vols 1-3, Conference Proceedings.

Wickart, M., Madlener, R., 2007. Optimal technology choice and investment timing: A stochastic model of industrial cogeneration vs. heat-only production. Energy Economics 29 (4).

Yang, M., Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., 2007. Evaluating the power investment options with uncertainty in climate policy. Energy Economics, In Press, Corrected Proof, doi:10.1016/j.eneco.2007.06.004.

Ådahl, A., Harvey, S., 2007. Energy efficiency investments in kraft pulp mills given uncertain climate policy. International Journal of Energy Research 31 (5).