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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. 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 wood fuel 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.

The aim of this paper is to present a systematic approach for analysis of the trade-off between economy and CO_2 emissions when investments are optimized under uncertainty. A methodology for identification of robust investments in energy efficiency under uncertainty [1–3] is here further developed to include multiple objectives and is then applied in a case study. The purpose is to illustrate how the previously published single-objective model can be extended to include both an economic and an environmental objective. Many uncertainties affecting investment decisions are related to future CO_2 emissions targets and policies, which implies that a method for optimization of both economic and environmental criteria will provide better information for decision-makers in industry to base the decisions on.

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. By reducing the use of fossil fuels, emissions are decreased on-site. Biomass is generally assumed to be CO_2-neutral; nevertheless, the reduction of wood fuel use will also lead to CO_2 emissions reductions, but in this case off-site, since reduced usage enables substitution of fossil fuels elsewhere. Also decreased imports or increased exports of electricity will affect the net CO_2 emissions.

The pulp and paper industry, from which the case study of this project is taken, is the fourth largest industrial energy user in the world [4], which makes it important in the progress to mitigate climate change. Cost-effective energy savings and potential CO_2 reductions have been identified in the pulp and paper sector in several studies [5–7]. 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. [1], 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 (see e.g. [8]). Multiobjective optimization has been used in combination with pinch analysis for the thermo-economic optimization of wood gasification systems [9-10] and solid oxide fuel cell systems [11], and for the trade-off between energy and capital costs in site-wide applications [12]. An extension to the traditional pinch technology to include several targets, called the Multi Objective Pinch Analysis (MOPA), has also been proposed [13].

Multiobjective optimization has also been used in other process integration studies, for example, in a methodology for pollution prevention where economic and environmental performance were optimized [14]. It has been used to find the optimal integrated design of a natural gas combined cycle plant with CO_2 capture, minimizing CO_2 emissions and electricity cost [15], and to find the optimal retrofit of a methanol process, maximizing income and minimizing depreciation [16]. There are also examples of process integration studies where not only two, but several conflicting criteria such as investment costs, fuel consumption, safety, and water recovery are taken into account [17].

There are also other applications of multiobjective optimization which are not concerning process integration, but well energy and industry. One example is the optimization of operation strategies of cogeneration systems, minimizing costs and emissions [18]. 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 [19, 20]. In addition to the mathematical programming methodologies using multiple objectives, there are also other methods for multi-criteria decision problems such as the Analytic Hierarchy Process (AHP) which, for example, has been used to evaluate power plant technologies with regard to seven criteria [21].

Heinrich et al. [22] 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.

Finally, there are several recent studies that show the importance of incorporating uncertainties into the optimization of energy investments. Some examples are studies that investigate the influence of uncertainties and timing for investments in power generation [23, 24], or the difference between market and policy uncertainty, also with application to the electricity sector [25]. Other studies concern investments in integrated gasification and combined cycle plants within an emissions trading scheme [26], or the choice between investment in combined heat and power or heat-only production for an industrial firm [27]. 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 [1].

3. Methodology

This study has been conducted using a methodology for optimization of investments in energy efficiency under uncertainty [1]. 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 mixed-integer linear programming (MILP) model for optimization under uncertainty (a stochastic programming model).

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. For a more detailed description of the optimization model for the single-objective case, including all constraints, see [3]. For literature on multiobjective optimization in engineering problems, see e.g. [28, 29].

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 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).

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:

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

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. Because discounting of emissions is unconventional, both discounting and no discounting are possible model settings through the choice of the r_E value. Tests have shown, however, that by choosing no discounting ($r_E = 0$), the optimization will give meaningless results. To understand this, consider first that cash flows are always discounted. With no discounting for emissions, a cheap way of improving the CO_2 emissions objective 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 are valued the same as if they were made today. This would imply that it is always better to postpone the investments in CO_2 reductions – that it is better to earn money now, and save the climate later. This has, unfortunately, been the philosophy of industry, and is exactly the reason we have landed up in the difficult situation of global warming. These kinds of results, where emission abatements are constantly postponed, are not our intention, nor is it what is asked for by those decision-makers in industry who are willing to use this kind of sophisticated methodology.

The recommendation is therefore to apply emissions discounting. Such a choice is in agreement with the political intention that calls for emissions reductions already today. If 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. By choosing the same value for the emissions discount rate as for the cash flow discount rate, the time preference discussed above will be cancelled out. More specifically, for a given emission-reduction investment project, the cost per kg of CO_2 avoided during the project lifetime will be the same – in present value – independently of when the investment project is initiated. Present value here refers to the value of the project discounted to today's units, as opposed to the value of the project at the time the project is initiated.

The optimization model enables the use of two different methods to solve the multiobjective optimization problem, the weighted-sum approach and the ε-constraint method. In this study, we have used the ε-constraint method, since our objective functions are incommensurable and of different magnitudes, which makes it difficult to determine the weights of the weighted-sum approach to obtain an even spread of solutions on the Pareto front. Furthermore, for non-convex function sets, as for example, for mixed-integer models as the one in this study, it is not always possible to find all solutions in the Pareto-optimal set using the weighted-sum approach [30].

4. The case study

The optimization model consists of a model of the pulp mill and an energy market scenario model.

The studied mill is a computer model of a typical Scandinavian chemical market pulp mill [31]. In energy-efficient mills of this kind, the by-products from the wood raw material are used as fuel and this is enough to cover the steam demand of the process. Hence, increased energy efficiency at the mill will not affect the on-site emissions of CO_2. It will, however, give an opportunity to export energy in the form of wood fuel, electricity, or heat, which then will lead to decreased emissions off-site. For input data and assumptions regarding the mill and the opportunities for energy efficiency, the reader is referred primarily to the previous paper by Svensson et al. [2].

The studied mill is assumed to be faced with a planned production increase [32]. The production increase will lead to an increase of black liquor flow to the recovery boiler, which is, in many cases, one of the bottlenecks in the process. The traditional approach to increase the production in such cases is therefore to upgrade the recovery boiler. Such an investment is substantial, but renders the possibility of also increasing the electricity production at the mill. An alternative approach, to avoid upgrading the recovery boiler, is to extract lignin from the black liquor before it enters the recovery boiler [32]. The lignin can then be exported for use as a wood fuel, 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. Thus, for lignin extraction to remain an interesting option, substantial steam savings are needed.

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 [33, 34]. In addition, the amount of available excess heat can be determined. Axelsson et al. [35] 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.

There is also potential to use low-pressure steam or excess heat of lower quality, such as hot water, for district heating deliveries. The potential naturally depends on whether there is a district heating system near the mill and what the alternative heat production is in that system. We assume here the presence of a small district heating system nearby since Jönsson et al. [36] showed a larger potential for profitable excess heat cooperation between mills and energy companies in small district heating systems (see [37] for data on and a description of that system).

The scenario model is constructed on the basis of five scenario blocks which are described below.

1A A 'business as usual' evolution of society (before 2015). Nordic market marginal price setting. Data from Sweden, the first quarter of 2006.

1B A 'business as usual' evolution of society (after 2015). Replaces block 1A after year 2015. European market marginal price setting. No increase in CO_2

emissions charges such as the price of CO_2 emission permits – corresponding to a decrease of the CO_2 emissions cap – or a CO_2 tax.

2A A 'moderate change' evolution of society (before 2020). The CO_2 emissions charge is increased compared to block 1A/B. The green power certificates are assumed to drop in price because of the higher CO_2 charge, which also promotes green electricity production. CO_2 capture and storage (CCS) is assumed not to be available for marginal electricity production.

2B A 'moderate change' evolution of society (after 2020). Replaces block 2A after year 2020. 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 blocks 2A/B. The green power certificates are, consequently, further reduced in price.

The parameter sets are generated using a tool for creating energy market scenarios [38]. The lignin price and district heating price are calculated based on the output from the scenario-generating tool [2]. The resulting data for the scenario building blocks are presented in Table 1.

Table 1: 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 wood fuel [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 CO2 capture and storage (CCS).
[c] Marginal use of wood fuel: 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). The reason why natural gas combined cycles (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 wood fuel is co-firing in CFB (Continuous Fluidized Bed) plants. To obtain a scenario block with a different marginal wood fuel user, green transportation certificates have to be introduced.

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. We therefore chose here not to include developments with low oil prices or developments with green transportation certificates and the uncertainties that are studied are thus only related to the future CO_2 emissions charges. It is, however, important to realize that the assumptions on marginal electricity production and marginal wood fuel use will have significant impact on the results.

We will assume a strategic view on investments, since that is the case for which uncertainties have the strongest influence on the results [2]. This is achieved by choosing a relatively low discount rate, r_C = 9% (r_E = r_C, according to the discussion in

Section 3) and a rather long economic lifetime, T = 30 years. This corresponds to an annuity factor of 0.1 year^{-1}, identified as reasonable for strategic decisions within the industrial cooperation research programme FRAM [31]. The economic lifetime and discount rate can and should be varied in a sensitivity analysis to see the results of different investment plan perspectives (see [2]). Here, this kind of analysis has been omitted to keep focus on the multiobjective, stochastic optimization methodology.

The five building blocks, 1A/B, 2A/B, and 3, are thus combined into five different development paths or scenarios that range over 30 years (see Figure 1). The paths, which were first suggested by Ådahl and Harvey [39], describe different developments regarding the attention to climate issues for the future.

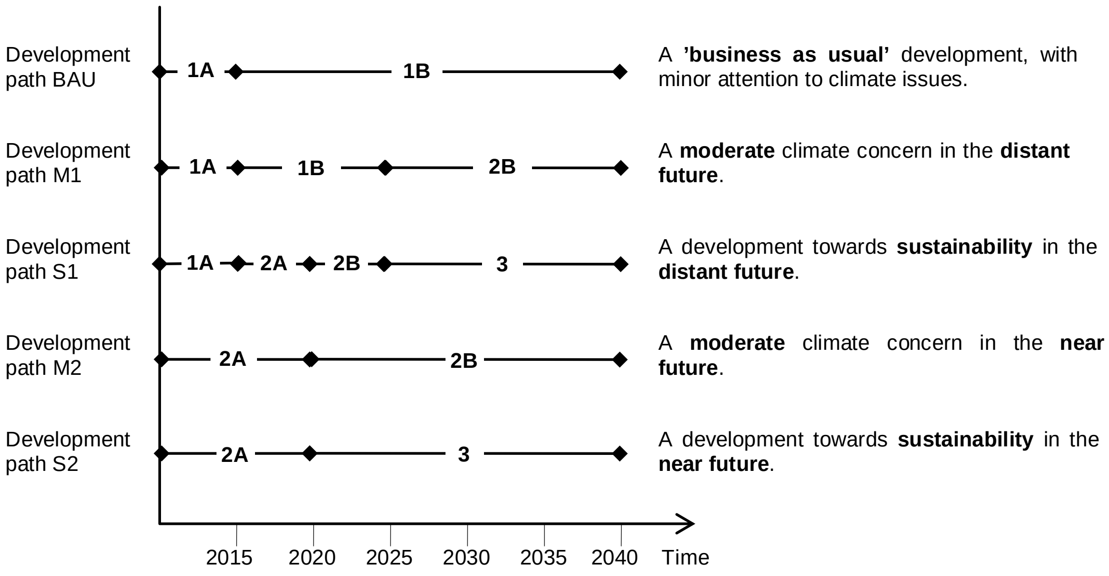

Figure 1: Development paths for energy market parameters.

5. Results and discussion

To illustrate the influence of making different assumptions regarding the probabilities for the scenarios, three different probability distributions are used (see Table 2). They represent different views on the future development of the energy market. It has previously been shown that the probability distribution can be varied quite substantially in this case without altering the economic optimum solution [2, 3]. Hence, no detailed analysis of the impact of varying the probability distribution is provided here.

Table 2: The three probability distributions used here.

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

All three probability distributions result in the same optimal solution when only the NPV 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 visualized in a Pareto graph (see Figure 2). This graph makes it clear how an increase of the CO_2 emissions reduction will affect the NPV. The Pareto graph shows the same kind of characteristics for cases 'A', 'B', and 'C'. As expected, an improvement of the CO_2 objective can be achieved at a lower loss in NPV at a lower CO_2 decrease level, since the most cost-effective CO_2-reducing measures are carried out first. Two extreme cases – one with probability one for BAU and zero for the rest, and one with probability one for S2 and zero for the rest – are also included in the graph for comparison.

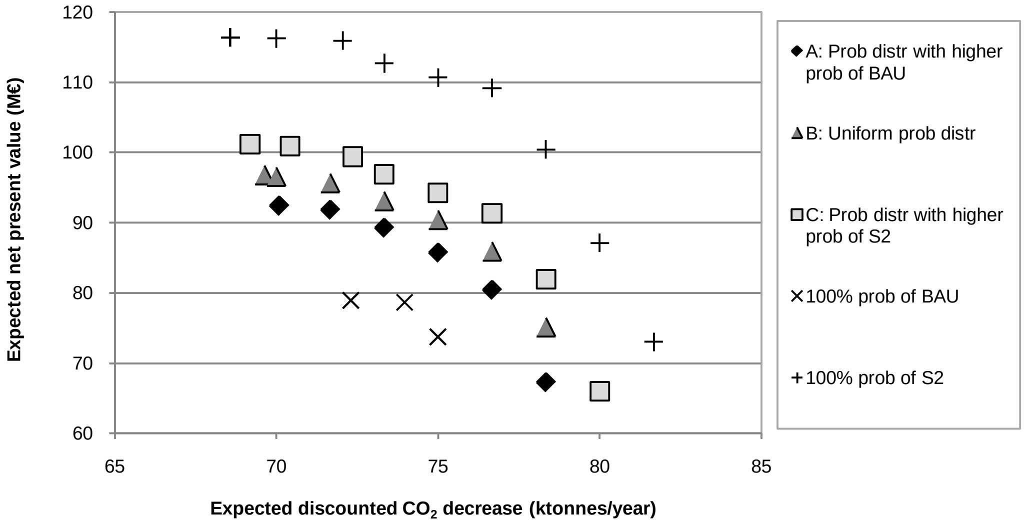

Figure 2: Pareto graph illustrating the trade-off between economic and environmental criteria (NPV and discounted CO_2 emissions) for two probability distributions. Because of the binary variables in the model, the Pareto curve between the computed points is not guaranteed to be continuous. Since the curve characteristics are unknown, only the computed points are indicated.

Figure 2 also illustrates a difference between the probability distributions. For distribution 'C', which represents higher probabilities for the sustainability scenarios, it is possible to achieve a higher NPV compared to 'A' and 'B' for the same CO_2 emission reduction. This is an expected consequence of the higher energy prices in the sustainable development paths.

The difference between 'A', 'B', and 'C' is, however, also explained by the system consequences of energy efficiency improvements in the three cases. Consider, for example, the difference in marginal electricity production for the different scenario building blocks presented in Table 1. Electricity generated at the mill 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 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.

Thus, there is a need of comparing the CO_2 emissions to some kind of target value, since the maximum achievable reduction might vary between scenarios even when the same energy efficiency measures are taken. According to Eq. (2), the CO_2 target is here defined as the maximum achievable emissions reductions independently of the cost-effectiveness of the measures. Hence, measures that are not considered to be of interest to include in the model, for example, because of a too high investment cost will, however, not be included in the target calculation either. 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 3 and we call this a target graph. It should be especially useful to illustrate the results in a target graph if the CO_2 targets are very different between the scenarios or if the probability distributions do not yield the same economic optimum. Here, 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 wood fuel 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 target solution being, for all paths, as will be shown below, characterized by high lignin extraction rates. The CO_2 emissions associated with lignin extraction are equal for all scenario blocks.

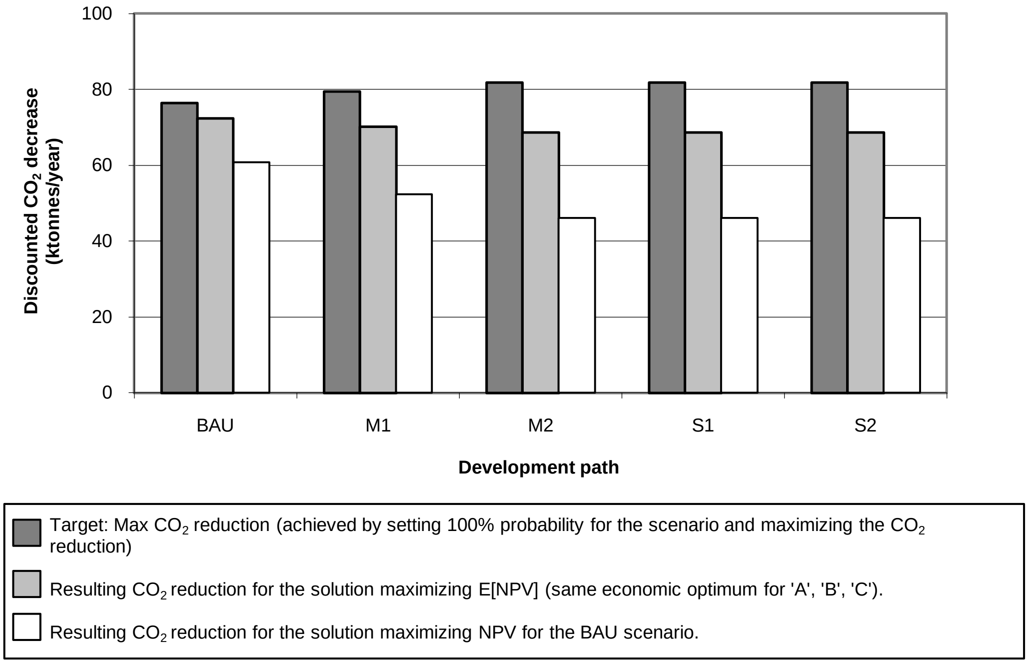

Figure 3: A target graph.

The target graph shows that the economically optimal solution for probability distributions 'A'–'C' 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. If the economic optimum was dominated by electricity production, the difference between the target and the economic optimum would be more significant. One such solution that is dominated by electricity production is the (deterministic) one that maximizes the NPV in the BAU scenario. The resulting CO_2 emissions reduction in that case is also included in Figure 3 for an illustrative comparison.

The investments characterizing the different solutions are shown in Figure 4. 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.

Where Figure 4 shows no distinct changes in initial investments, the increase in CO_2 emissions reductions are achieved through either a changed allocation of investments within the categories or through investments made at a later stage. The detailed investment plan (not only Figure 4) reveals that increased CO_2 emissions reductions are in fact achieved through a combination of later investments in lignin extraction and a shift in the supply of district heating. 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 involve changes connected to district heating. These investments are not cost-effective in the other scenario building blocks.

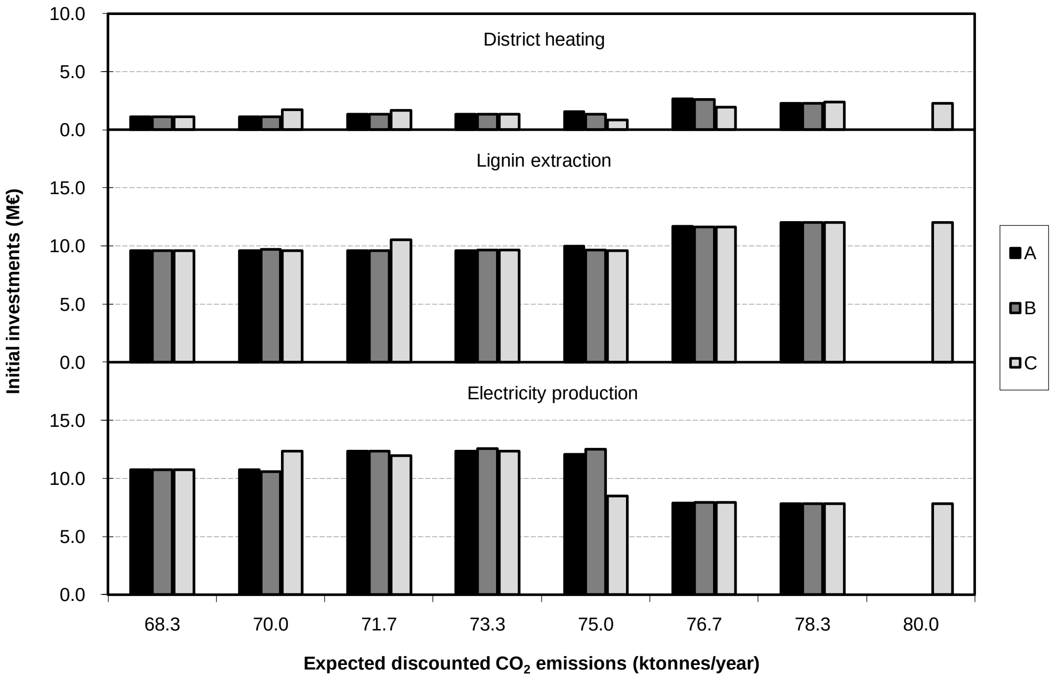

Figure 4: Changes in initial investment (excluding the investments in steam savings) as a function of increasing requirements on the CO_2 emissions reductions. Alternatives ‘A’, ‘B’, and ‘C’ refer to the probability distributions in Table 2.

The CO_2 objective is, according to Eq. (2), the expected value of the discounted CO_2 emissions over all future scenarios. Thus, 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 ensure that improvements are made for all scenarios, the optimization problem can, using the ε-constraint method, be reformulated with one CO_2 objective for each path. 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 (see for example [40]).

6. Conclusions

In this paper, we present a multiobjective approach for the optimization of investments in energy efficiency under energy market uncertainty. The proposed approach is based on a previously presented methodology for optimizing such investments under uncertainty with respect only to an economic objective [1]. We show that the multiobjective 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 propose 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 wood fuel 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 for reasonable probability distributions is quite close to what is maximally achievable. This indicates a robustness of this economic optimum solution, confirming the results of previous work [2, 3].

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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