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Climate Change: Optimization of Response Strategies

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The development of climate change response strategies is expected to remain an important issue in the next few decades. The use of optimization techniques might serve as a helpful guide in this process. Although, in recent years, a number of studies have focused on optimization techniques, the optimization models do not fully employ the dynamics of climatic and economic systems. In this paper a heuristic is introduced that combines an integrated simulation model and an optimization technique (local search). This approach may be considered as a first step towards a more comprehensive and systematic analysis of climate change response strategies in a dynamic setting described by a simulation model. Results of a number of experiments in which the heuristic is applied to the integrated global assessment model TARGETS are discussed.

Key words: optimization, simulation, climate change

INTRODUCTION

Since the 1980s, the possibility of a human-induced global climate change has been regarded as one of the most important global environmental problems, and such a change can have profound economic and social implications for future generations all over the world. International efforts have therefore been directed at the development of response strategies which mitigate the risks associated with anticipated climate change (UN, 1992). Optimization might serve as a helpful guide in the search for appropriate response strategies. In this article, a heuristic is discussed that can be used for this purpose.

Mathematical models have made an important contribution to the understanding of the climate change problem, and vary from General Circulation Models (GCMs) to integrated assessment models. The former rely upon mathematical equations of atmospheric, oceanic and terrestrial processes, which are based on the laws of physics. The Earth's atmosphere is divided into gridboxes horizontally and consists of several layers vertically. Extensions of GCMs are 'Coupled' GCMs (CGCMs) which are coupled ocean/atmosphere circulation models. These (C)GCMs are capable of simulating virtually all important climatic variables (IPCC, 1992). (C)GCMs are often employed to predict the equilibrium surface temperature increase following a doubling of carbon dioxide concentration.

An important drawback of (C)GCMs is that the necessary simulation runs require a vast amount of computing time. Integrated assessment models have therefore been developed as scientifically-based policy models describing the climatic system on a global scale. Simplified versions of specialized models from various scientific areas are linked together to describe the causes, mechanisms and effects of climate change. Although integrated assessment models do not describe the complex climate system in full detail, they can be used interactively in order to estimate the effects of various scenarios. Examples of such models are IMAGE (Rotmans, 1990), STUGE (Wigley *et al.*, 1991), ESCAPE (Rotmans *et al.*, 1994a) and TARGETS (Rotmans *et al.*, 1994b).

The models described above simulate the cause–effect chain (Fig. 1, perspective 1) and scan the future according to possible scenarios. Given a set of policy targets, optimization techniques may be used to derive suitable strategies (Fig. 1, perspective 2). However, simulation models as described above are too complex to be used in an orthodox optimization approach. Another strain of mathematical models, namely optimization models, has been developed in order to identify 'optimal' response strategies (see e.g. Nordhaus, 1992, 1993; Tahvonen *et al.*, 1993). Although all mathematical models are simplifications of reality, optimization models require simplifications so that these

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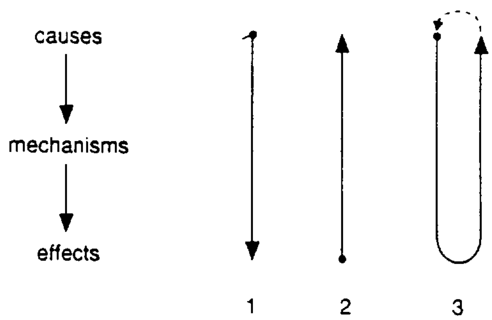


Fig. 1. Different perspectives on the use of models: (1) simulation: effects of scenarios are estimated using (C)GCMs and integrated assessment models; (2) optimization: search for optimal strategy given constraints on effects using parameterized optimization models; and (3) heuristic approach (this study): search for an optimal strategy using an optimization technique (local search) and a simulation model (integration assessment model) in an iterative manner.

models do not fully employ the system dynamics. This disadvantage of optimization models may limit its use in decision-making concerning climate change related problems.

Nevertheless, optimization in itself could prove to be useful in the development of response strategies. In this paper a heuristic optimization approach is introduced which combines an optimization technique (local search) and an integrated assessment model (Fig. 1, perspective 3). This approach takes the dynamics of the system into account and yields (local) optimal strategies. Such an approach might prove to be an important step towards a more comprehensive and sophisticated analysis of climate change response strategies in a dynamic setting described by a simulation model.

The organization of this article is as follows: after the climate change problem is discussed briefly, the methodology adopted for the optimization approach is presented. A number of policy-evaluation experiments are derived using the integrated global assessment model TARGETS of which a short description has been given. Results of an attempt to solve an illustrative optimization problem are discussed, whereby the objective is to maximize economic output given a restriction on the (rate of) temperature increase. Finally, a number of concluding and evaluative remarks are made.

CLIMATE CHANGE

The greenhouse effect is a natural phenomenon. It is caused by long-wave terrestrial radiation, which has been re-emitted from the surface of the Earth, being trapped in the atmosphere by the presence of clouds and trace gases, i.e. those capable of absorbing radiation, such as water vapour (H_2O), carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), halocarbons and ozone (O_3). Without this natural greenhouse effect the mean surface temperature would have been about 33 °C lower (IPCC, 1992). However, there is growing evidence that the greenhouse effect is enhanced by anthropogenic emissions of greenhouse gases. It is known that the increases in atmospheric concentrations of carbon dioxide, methane, nitrous oxide, chlorofluorocarbons (CFCs) and other trace gases which have occurred during recent decades are largely attributable to human activities. These increases are expected to result in a rise in the global mean surface temperature of the Earth. In informed circles, the only debate is about the extent, rapidity and geographical distribution of such a rise in temperature.

The most important greenhouse gas apart from H_2O is CO_2, which is expected to be responsible for more than one-half of the potential enhanced greenhouse warming. The main present sources are the combustion of fossil fuels (6 GtC/yr)* and land use changes (1–2 GtC/yr) (IPCC, 1992).

The net energy input in the lower atmosphere results in an additional warming of the Earth's surface. Over the last 100 years the global mean surface temperature is believed to have increased by between 0.3 and 0.6 °C (IPCC, 1992), although it is not known to what extent anthropogenic

*GtC = gigatons (10^{15} grams) of carbon.

emissions have caused this increase. Climate model experiments show that an instantaneous doubling of the atmospheric CO_2 concentration would lead to an increase in the average surface temperature of between 1.5 and 4.5 °C† (IPCC, 1992).

The future temperature increase depends on current uncertain trends which are significantly influenced by policy measures, as well as being determined by a complex system of feedback mechanisms. Time lags in the climate system's response to changes imply that some degree of future climate change is inevitable.

Climate change could have profound economic and social consequences and major threats include sea level rise, enhanced erosion, salt intrusion, changes in agricultural yields and increases in vector-borne diseases. On the other hand, response policies aimed at reducing emissions of greenhouse gases will certainly also affect the economies of modern societies, since they are largely dependent on fossil fuels. This dilemma is the main issue in developing policy strategies.

METHODOLOGY

Basic philosophy

It is virtually impossible to envisage an unequivocal optimal solution for the global climate change problem. Moreover, it is not even clear how the optimization problem should be conceptualized. The numerous objectives, which might be taken into account when developing response strategies, include goals such as economic efficiency, ecological sustainability and equity with respect to inter-regional and inter-generational levels. In view of such a broad spectrum of objectives it would seem a virtually impossible task to formulate an optimization problem for climate change. However, since optimization problems can be formulated from various perspectives, they can be used to explore the solution space in search of specific policy strategies.

Previous optimization studies in the field of climate change used highly parameterized models (see e.g. Nordhaus, 1992, 1993; Tahvonen *et al.*, 1993). These models were calibrated using the outputs of (various) simulation models. However, since these optimization models are unable to take account of the complex behaviour of the system, they can only yield valid scenarios for a certain subdomain within the solution space. Although integrated assessment models also have their limitations, their dynamic system approach enhances their ability to accommodate changes in decision variables.

When simplified models are used the mathematical problems involved in finding the optimum which is to be preferred among all local optima (global optimum), can be rather intractable in practice. Using more sophisticated models it might be impossible to find the global optimum. Since evaluating the risks of climate change involves dealing with high degrees of uncertainty, the search for such an optimum would be a waste of time and effort, and the quest for the global optimum may be abandoned in good conscience.

Given the practical difficulties discussed above, it seems appropriate to discuss the deployment of optimization techniques which may thus be used in combination with an integrated assessment model in order to identify 'optimal' policy strategies. The aim of this study, which sets it apart from other approaches is, therefore, to enable identification of local optima using a simulation model (in this case an integrated assessment model) rather than searching for a global optimal solution with the help of a highly parameterized model.

The heuristic

The general optimization problem considered in this article is a maximization of the objective function $F(\mathbf{x})$ which values the 'state of the world' over some predetermined time period subjected to a set of constraints c_i related to climate change which are preferential according to a climate change policy.

†In this study a best guess value of 2.5 °C is used (IPCC, 1992).

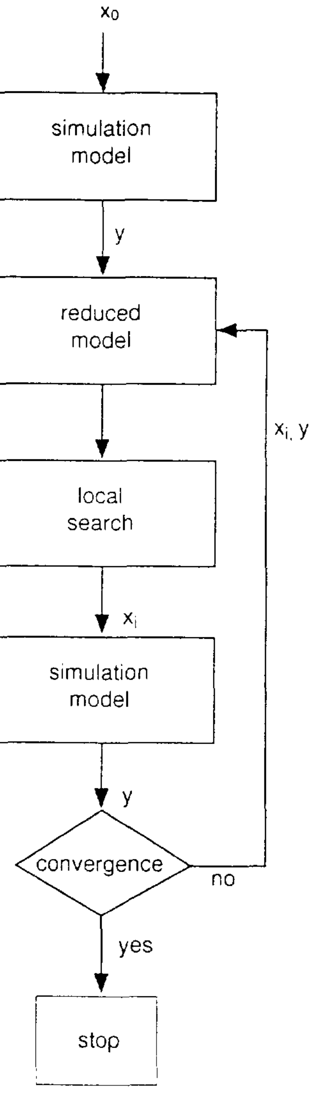


Fig. 2. Heuristic of local search algorithm.

$$\max_{\mathbf{x}} F(\mathbf{x})$$
$$\text{s.t.} \qquad (1)$$
$$G_i(\mathbf{x},t) \leq c_i\,(t) \qquad \forall i,t,$$

where $\mathbf{x}$ is a vector of decision variables (e.g. carbon tax policies, reforestation, investments in renewable energy and recycling options) and t denotes time. Since a simulation model is used for optimizing this problem, it cannot be expressed in analytical formulas. In fact, the values of $F(\mathbf{x})$ and $G_i(\mathbf{x},t)$ are outputs of the simulation model given an input of $\mathbf{x}$.

The heuristic which is deployed here to solve problem (1) is an adapted version of Multistart (Janssen *et al.*, 1992), a stochastic optimization method which involves several local searches‡ being started at random points until a sto pping rule has been satisfied (Rinnooy Kan and Timmer, 1989). In the general case, starting points are drawn from a convex and compact set which contains the global optimum. In order to arrive at a solution within an acceptable runtime a number of adaptations has been made to enable a simulation model to be used in conjunction with an optimization approach.

‡*By local search we mean an optimization algorithm leading to a local optimum of a nonlinear optimization problem.*

The heuristic is based on the following two devices:

1. The start of a fixed number of local searches at selected starting points $\mathbf{x}_0$. This enables a priori knowledge, such as present or proposed (policy) scenarios, to be incorporated into the optimization. The consequence of this approach is that independent of the degree of optimality, the local optima found are improvements on present or proposed scenarios. Furthermore, starting with only a fixed number of local searches will reduce runtime compared to a stochastic approach like Multistart.
2. The use of a reduced version of the simulation model. A reduced model is defined here as a set of equations that represent the core of the model. The manner in which the variables are related remains the same as in the simulation model. A number of variables which are endogenous in the original simulation model are treated as exogenous variables in the reduced model, and consequently only a small number of the equations used in the original simulation model need to be used. The optimization problem can be reformulated as follows:

$$\begin{gathered}\max_{\mathbf{x}} f(\mathbf{x},\mathbf{y}) \\ \text{s.t.} \\ g_i(\mathbf{x},\mathbf{y},t) \leq c_t(t) \qquad \forall i,t,\end{gathered} \tag{2}$$

   where $f(\mathbf{x},\mathbf{y})$ and $g(\mathbf{x},\mathbf{y},t)$ are outputs of the reduced model and where $\mathbf{x}$ represents the decision variables and $\mathbf{y}$ the exogenous variables. Observe that in this formulation $\mathbf{y}$ is not a variable but represents the estimated outcomes of the simulation model. Such a reduced model is only valid for a subdomain of the solution space. Therefore, the values of $\mathbf{y}$ will be updated several times during the optimization.

The heuristic consists of a limited number of local searches (Fig. 2). Every local search is started in a selected start scenario $\mathbf{x}_0$. The simulation model is run using $\mathbf{x}_0$ as input and estimated values for the exogenous variables $\mathbf{y}$ of the reduced model. Using a local search routine, a local optimum $\mathbf{x}_i$ is found for the problem formulated in (2). The simulation model is rerun to check whether the values of $\mathbf{y}$ belonging to $\mathbf{x}_i$ differ significantly from the values of $\mathbf{y}$ belonging to $\mathbf{x}_{i-1}$. If the values indeed differ significantly, the local search routine is rerun using new values of $\mathbf{y}$ and starting in $\mathbf{x}_i$, and if they do not, a local optimum of problem (1) is deemed to have been found.

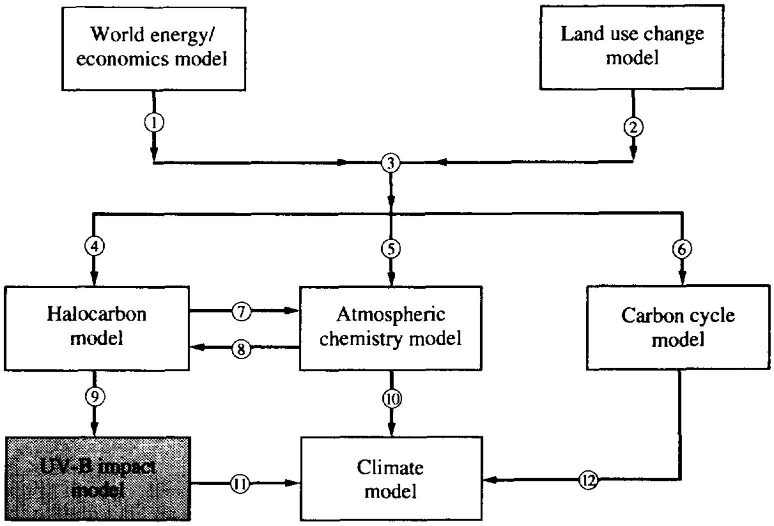
CASE STUDY

Introduction

The Dutch National Institute of Public Health and Environmental Protection (RIVM) is currently developing an integrated global assessment model entitled TARGETS (Tool to Assess Regional and Global Environmental and health Targets for Sustainability) which links models from various scientific areas (Rotmans *et al.*, 1994b). This integrated system approach is designed to operationalize the concept of sustainable development from a global perspective for a simulation period from 1900 up to 2100. The model itself contains several submodels:

(i) a human system model, which describes the demographic and health state dynamics;
(ii) an economy/resources, model which describes the driving forces that create environmental pressure (a submodel based on the World 4 model (Vries *et al.*, 1993), itself a successor to the World 3 model developed by Meadows *et al.* (1974));
(iii) a land model in which the causes and effects of land use changes are incorporated;
(iv) a global environmental change model which describes the global environmental system (Elzen and Rotmans, 1993) and which is an extension of the Integrated Model to Assess the Greenhouse Effect IMAGE (Rotmans, 1990; Elzen, 1993);
(v) a model of socio-economic effects caused by a global change.

In this case study, a part of the TARGETS model is used to provide an illustration of the



1 Energy-related emissions of CO_2, CH_4, CO, NO_x and N_2O
2 Emissions of CO_2, CH_4, CO, NO_x and N_2O by land use changes, agricultural activities, land fills and natural sources
3 Emissions of CO_2, CH_4, CO, NO_x and N_2O
4 Production of halocarbons
5 Emissions of CH_4, CO, NO_x and N_2O
6 Emissions of CO_2
7 Concentration of halocarbons
8 Concentration of OH
9 Stratospheric ozone depletion
10 Concentration of non-CO_2 greenhouse gases
11 Radiative forcing due to lower stratospheric ozone losses
12 Concentration of CO_2

Fig. 3. Part of TARGETS model as used in this study.

optimization approach (Fig. 3): namely a preliminary version of the energy model, which is a part of the economy/resource model and an experimental version of the global environmental change model (Elzen, 1993). The basic structures of the separate models, which are interesting for this study, are briefly described in the next section.

Model

The energy model. The energy submodel simulates the use of fossil fuels (coal, oil and gas) and alternatives as well as simulating ways of substituting energy end-use for capital (Vries *et al.*, 1993). It incorporates some 130 equations and is divided into three parts: an energy demand model; an energy transformation model; and a supply model. Depletion of stocks of fossil fuels is governed by long-run supply curves. New investments are based on expected profitability. Energy prices are derived from cost (supply–demand disequilibrium) which in turn is based on depletion and learning-by-doing dynamics. If an alternative enters the market, its relative price will determine the degree of market penetration.

The climate change model. The climate change model incorporates some 250 equations and is a composite of autonomously-functioning models: an atmospheric chemistry model; a carbon cycle model; a climate model; and an ozone model (Elzen, 1993). The carbon cycle is modelled as a dynamic system whereby flows of carbon involving the atmosphere, oceans and terrestrial biosphere are simulated. The methane concentration is derived from the global CH_4-CO-OH cycle, while other non-CO_2 trace gases are removed from the atmosphere at constant rates. The total change in radiative forcing results in a global mean surface temperature change. The model also takes account of a number of interactions which have a bearing on the relationship between stratospheric ozone depletion problem and the climate change problem.

Problem formulation

Since climate change policy has numerous objectives, any formulation of an optimization problem will necessarily neglect specific aspects. Previous optimization studies used various problem formulations. Nordhaus (1992, 1993) maximizes the discounted sum of the utilities of per capita consumption using a control rate on emissions as a decision variable. Given this goal, he distinguishes several problems that differ in their constraints (e.g. no constraints, emissions stabilized at 1990 levels and an upper limit of total temperature increase of 1.5 °C from 1900). Furthermore, he considers a cost/benefit approach using a damage function related to temperature change. Tahvonen *et al.* (1993) distinguish between a cost-oriented strategy (cost/benefit analysis) and a target-oriented strategy (maximization of utility given temperature constraints) using emissions as decision variables. The formulations used in these studies cover only a small part of the range of possible problem formulations. They do not take account of ethical issues (Arge *et al.*, 1982), uncertainties (Dowlatabadi and Morgan, 1993) and multicriteria approaches.

A simplified representation of the complex problem of climate change is employed in this case in order to enable the presentation of preliminary results yielded by the heuristic method. The results are not relevant to policy at this stage in view of the preliminary state of the TARGETS model and the limited number of experiments conducted. A more comprehensive analysis of the optimization approach to a number of optimization problems is in preparation. This analysis will also include a sensitivity analysis to estimate the consequences of the major uncertainties inherent in the development of climate change response strategies. In this study, best-guess values are used for the parameters within the TARGETS model.

The case under consideration is one in which economic activities are restricted by an environmental constraint, since in the interests of sustainability a limited global mean temperature increase is allowed. In the first instance, the absolute temperature limit of 2 °C above pre-industrial global mean temperature (AGGG, 1990) is used, a level that can be seen as an upper limit beyond which risks of considerable damage are expected to increase rapidly. Although the scientific underpinning of this criterion is weak, it is nevertheless the best available.

Carbon tax policies are selected as one of the instruments by means of which this goal might be realized. Such policies increase the prices of fossil fuels and, therefore, discourage their use while making the use of alternative fuels more attractive. The increase in energy prices will lower the demand for energy, causing a fall in economic output.

From an economic perspective, decision-makers might wish to meet the constraint with minimal loss of economic activities. Maximization of industrial output,§ which is used here as an indicator for Gross National Product, is used as the objective function.

For the study of carbon tax policies a time period between 1993 and 2100 is considered. Let z_t be the carbon tax level in the year $t (t = 1993, \ldots, 2100)$. Let $\mathbf{z} = [z_t]_{t=1993,\ldots,2100}$ be a vector characterizing the carbon tax policy. For simplicity's sake, tax levels are assumed to change linearly over fixed time intervals during the period under consideration. The following time intervals are used according to IPCC (1992): $[T_0,T_1], \ldots, [T_3 T_4], T_0 = 1993,\ T_1 = 2000,\ T_2 = 2025,\ T_3 = 2050,\ T_4 = 2100$. The tax level is assumed to change linearly during $[T_k, T_{k+1}]$ where we denote the tax level in year T_k by x_k. The choice of $\mathbf{x} = [x_k]_{k=0}$ together with the known value of the initial tax level z_0 at time 1993, determines tax level z_t. From now on we would like to consider x_ks as the decision variables that determine z. Note that the input for the simulation model is a strategy z, which is determined by $\mathbf{x}$.

§Industrial output is the total value of goods produced by the industrial sector. It consists of consumption goods as well as investment goods. In the present version of the energy model industrial energy demand is the only factor modelled. Energy demand associated with agriculture, services and mining activities is allowed for by reference to exogenous trends.

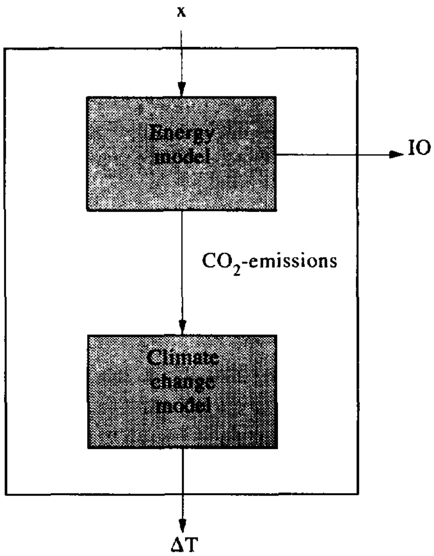


Fig. 4. Inputs and outputs of simulation model as used in this study.

The problem is not defined in terms of analytical formulas, but rather in terms of outputs of the simulation model (Fig. 4). The carbon tax is used as an input for the energy model which estimates industrial output and fossil CO_2 emissions. These emissions in turn serve as inputs for the climate assessment model which calculates the temperature increase.|| The optimization problem can now be formulated as follows:

$$\max_{\mathbf{x}} \sum_{t=1993}^{2100} IO_t(\mathbf{x})$$

$$\text{s.t.} \tag{3}$$

$$\Delta T_t(\mathbf{x}) \leq \Delta T_{max} \qquad t = 1993, 1994, \ldots, 2100,$$
$$\mathbf{x} \geq 0$$

where:

IO_t = Industrial output (in bn \$);
ΔT_t = Change in global mean surface temperature since 1900 (in °C);
ΔT_{max} = Maximum absolute global mean temperature increase since 1900 (in °C);
$\mathbf{x}$ = Carbon tax (in \$/tC).

The reduced version of the simulation model consists of the energy model and a number of equations borrowed from the climate change model. Since a preliminary version of the energy model is the only version available, no reduced version of this part of the model has yet been derived. Only six equations from the climate assessment part of the simulation model were used to estimate the temperature change (see the Appendix for details). These equations incorporate five variables borrowed from the simulation model which are treated as exogenous in the reduced version.

The solution space can be further tightened, by including a 'rate of change in global mean temperature' constraint. According to AGGG (1990) a maximum rate of increase of 0.1 °C per decade is allowed, which is still admissible for adaptations of ecosystems. Because of delays in the climate system, the 'rate of change in temperature' target cannot be reached in the next decades. Therefore, the constraint on the relative change is set from 2010 to 2100.

||Other trace gases, both from fossil fuel combustion and other anthropogenic sources are assumed to follow the Business-as-Usual scenario (no climate policy implemented).

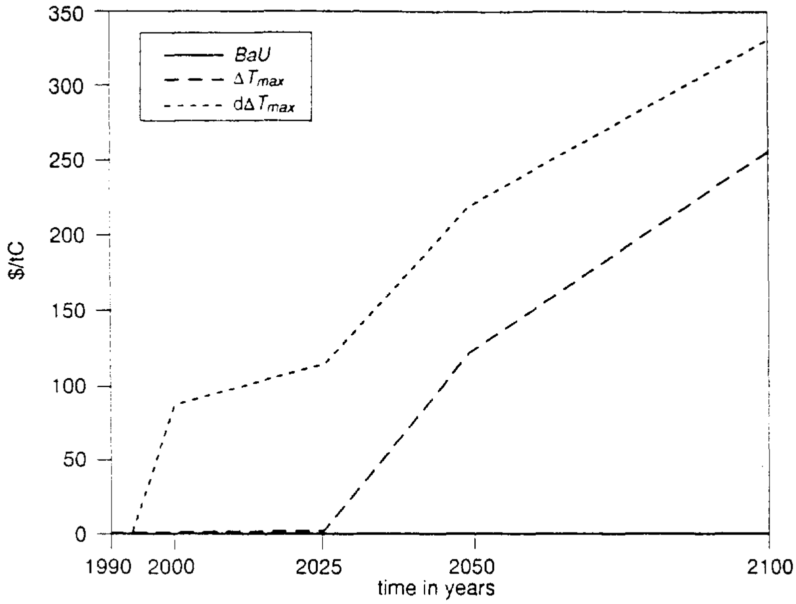


Fig. 5. Carbon tax policies.

$$\max_{\mathbf{x}} \sum_{t=1993}^{2100} IO_t(\mathbf{x})$$

$$\text{s.t.} \tag{4}$$

$$\begin{aligned} \Delta T_t(\mathbf{x}) &\le \Delta T_{\max} \quad & t &= 1993, 1994, \ldots, 2100, \\ d\Delta T_t(\mathbf{x}) &\le d\Delta T_{\max} \quad & t &= 2010, 2011, \ldots, 2100 \\ & & \mathbf{x} &\ge 0 \end{aligned}$$

where:
$d\Delta T_t$ = Rate of change in global mean surface temperature (in °C per decade);
$d\Delta T_{\max}$ = Maximum rate of global mean temperature increase per decade (in °C per decade).

Results

Introduction. Two carbon tax reference scenarios were defined for a number of experiments with the heuristic. For each of the scenarios a local search¶ is started. The first scenario is the Business-as-Usual scenario (IPCC, 1991), which is a continuation of current trends. A policy scenario based on the Accelerated Policies scenario (IPCC, 1991), which involves a shift towards non-fossil fuels, is adopted as the second reference scenario. The carbon tax scenarios are given in $ per tC for the years 2000, 2025, 2050 and 2100 (see also Section 4.3):

Business-as-Usual scenario (BaU) $\mathbf{x}_0 = [0, \ 0, \ 0, \ 0]$;
Accelerated Policies scenario (AP) $\mathbf{x}_0 = [0, \ 36, \ 51, \ 51]$.

These scenarios envisage an average annual growth rate of industrial output for the period from 1993 till 2100 of 1.9 and 1.2%, respectively, while the average global temperature increase in 2100 relative to 1900 is 3.6 and 2.1 °C, respectively.

'Change in temperature' target. If the 'change in temperature' constraint is to be met no carbon tax policy would have to be implemented until 2025, after which the (local) optimum carbon tax policy would feature an increasing tax level (Fig. 5). This tax policy causes a lower growth rate in industrial output because of the increase in fossil fuel prices by 3–10 times which increases energy

¶The Powell method is used as local search routine (Press *et al.*, 1988).

prices by about 40%. This increase lowers energy demand and causes extra investments in the energy sector to switch to alternative fuels. This results in an average growth rate in the optimal solution of about 1.3% per year, which is about 0.5% per year lower than in the Business-as-Usual case.

Nordhaus (1992) found that an optimal carbon tax path for a 1.5 °C maximum temperature increase constraint implies increases to around 200 \$/tC as early as 2000 and to 700 \$/tC by 2050 before levelling off at about 800 \$/tC in 2100. These tax levels are much higher because of a lower uppervalue constraint and because the use of alternatives (e.g. biofuels) is not associated with any physical constraints in the preliminary version of the energy model as used in this study.

The value of the objective function is about 15% higher for the optimal solution compared with that of the Accelerated Policies scenario, which narrowly fails to meet the 'change in temperature' constraint. Although the average temperature increase will be below 2 °C for this local optimum (Fig. 9) the 'rate of change in temperature' target is still violated for several decades after 2010 (Fig. 10).

'Rate of change in temperature' target. If a constraint is set on a rate of temperature increase from 2010 till 2100 of 0.1 °C per decade, the carbon tax policy will change significantly (Fig. 5). The tax already increases fossil fuel prices by about 4–10 times by 2000. By changing the fuel mix the average energy price increase is about 50%. The high tax levels necessary to meet the constraint, significantly reduce the growth of industrial output. This growth rate decreases by 1.0% per year compared to the Business-as-Usual case (Fig. 6).

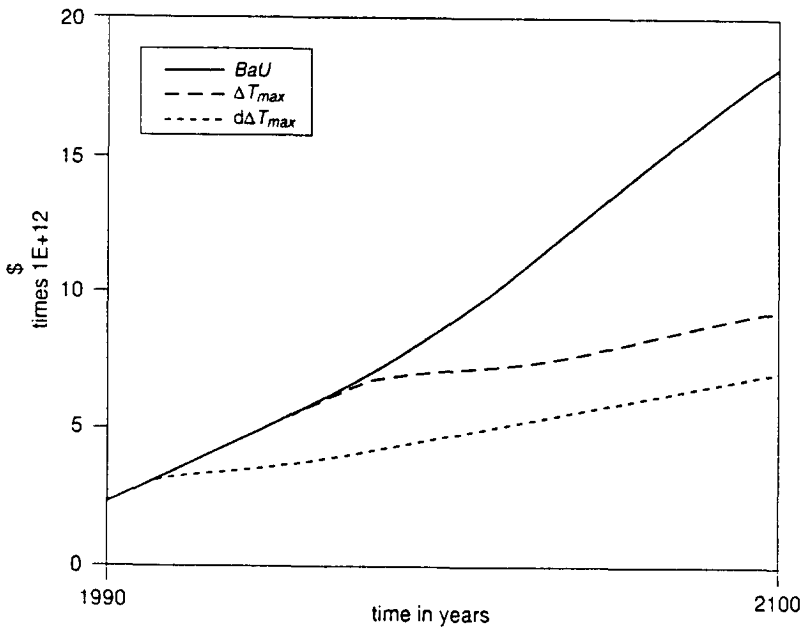


Fig. 6. Industrial output.

Figure 10 shows that some latitude is still left to meet the 'rate of temperature increase per decade' constraint. This is caused by the fact that fuel use allocation is based on relative prices and not on cost minimization. Therefore, it may happen that if carbon tax falls after 2050 the investment costs increase in order to re-introduce fossil fuels.

Characteristics of the optimization approach. The heuristic approach is compared with the case in which the simulation model is run for each function evaluation of the local search routine. Using the heuristic, the simulation model need only be run several times (Tables 1 and 2). This means that convergence** of the exogenous values y of the reduced model occurs only in several iterations. The number of times the simulation model is run when a straightforward local search is used is much larger. The number of times the reduced model is run in the heuristic is larger than in the

**In fact, convergence of the values of the exogenous variables y cannot be proved. However, the difference between y from two iterations remains within the tolerance level (1%) after several iterations.

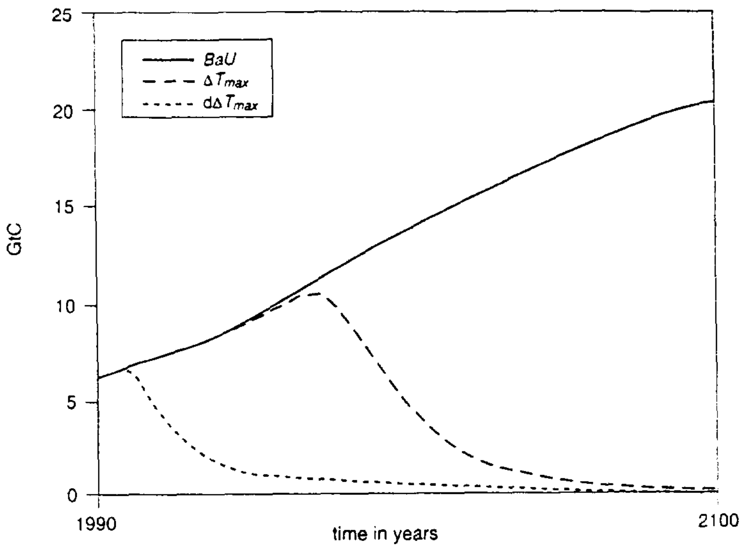


Fig. 7. Fossil CO_2 emissions.

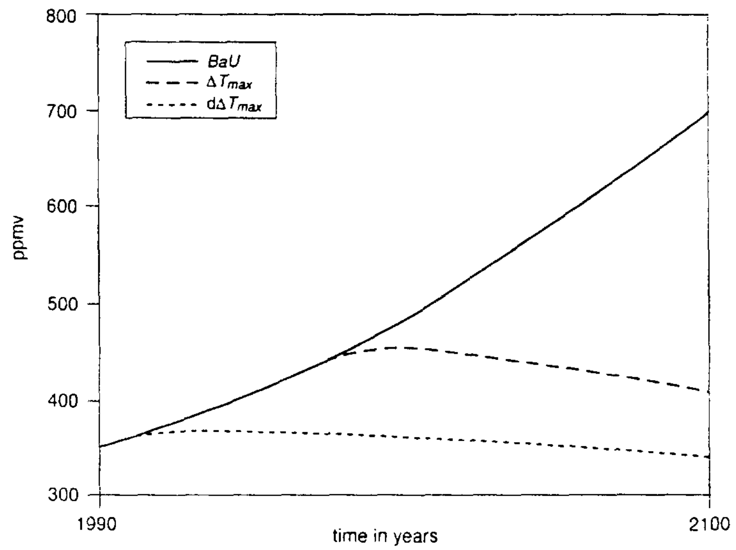


Fig. 8. CO_2 concentration.

straightforward local search, because the heuristic consists of several local searches in order to find the correct values of $\mathbf{y}$. However, because the reduced model requires a much smaller amount of runtime, the heuristic finds the optima in less runtime than the straightforward case.

Note that a priori knowledge seems to reduce the number of function evaluations, because starting with an $\mathbf{x}_0$ equal to the BaU scenario will in most cases require more function evaluations than starting with an $\mathbf{x}_0$ equal to the AP scenario.

The fact that the solutions are not all the same for each problem may be caused by the fact that different local optima may exist (Table 1) and because a minor error may be made while using the reduced version (Table 2).

CONCLUSIONS

It is a utopian dream to suppose that an optimal response strategy for climate change can be found, but optimization techniques can nevertheless be a helpful guide for the development of response

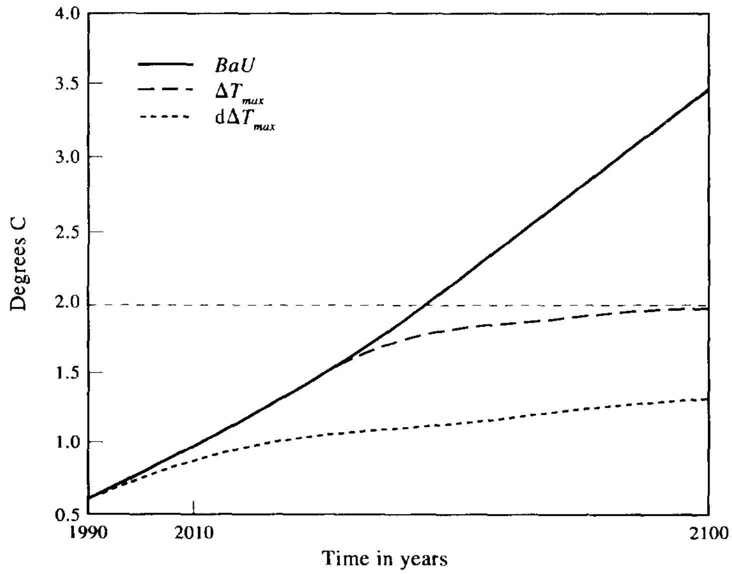


Fig. 9. Change in global mean surface temperature.

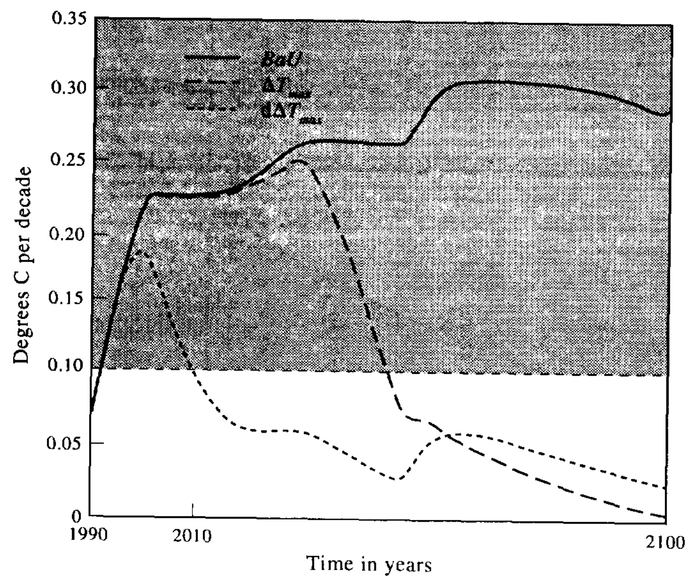


Fig. 10. Rate of change in global mean surface temperature.

strategies. In contrast to other studies, which use highly parameterized models, this paper presents an optimization approach which uses an integrated assessment model in order to search for (sub)optimal strategies. The approach is based on local searches started in selected reference scenarios. To reduce the number of runs of the simulation model, a reduced version of the simulation model is used. By updating values of the exogenous variables of the reduced model during the local search, a solution is found for the original problem. Indeed, although this approach will probably not succeed in finding the global optimum, better solutions than present policies can always be found by starting in chosen reference scenarios.

Some first experiments are derived using the climate change modelling part of the preliminary version of the TARGETS model. A more comprehensive study of properties of the heuristic is in preparation, including a sensitivity analysis of the optimal response strategies. A major topic for the near future will be the use of the heuristic for several types of problem formulations including the

Table 1. Solutions featuring a change in absolute temperature constraint. For every local search the value of the objective function (ΣIO, in \$ billions) is given as well as the optimal tax policy (**x** in \$/tC). This is given for the heuristic, which uses simulation models to update exogenous variables of the reduced model, as well as for the straightforward local search, in which the simulation model is simply run for each function evaluation

Results/ref. scenario	BaU	AP
Heuristic		
ΣIO	890331	893957
x	[0, 0, 151, 162]	[0, 0, 141, 193]
No. runs reduced version	14780	4001
No. runs simulation model	18	5
Straightforward local search		
ΣIO	893250	876343
x	[0, 0, 139, 191]	[0, 7, 106, 206]
No. runs simulation model	1895	1586

Table 2. As in Table 1 including solution for the rate of temperature increase constraint

Results/ref. scenario	BaU	AP
Heuristic		
ΣIO	659097	659110
x	[120, 114, 247, 354]	[120, 114, 247, 355]
No. runs reduced version	5280	3853
No. runs simulation model	7	6
Straightforward local search		
ΣIO	646558	646546
x	[161, 118, 272, 381]	[161, 118, 273, 383]
No. runs simulation model	746	2796

inclusion of uncertainty. Although this article has introduced the approach by referring to relatively few experiments it is expected that this approach is a first step towards a more comprehensive and sophisticated analysis of climate change response strategies.

REFERENCES

AGGG (1990). *Targets and Indicators of Climate Change*, F. Rijsberman and R. J. Swart (Eds). Report of Working Group II of the Advisory Group on Greenhouse Gases (AGGG), Stockholm Environmental Institute, Stockholm, Sweden, ISBN 91-88116-21-2.

Arge, d', R. C., Schulze, W. D. & Brookshire, D. S. (1982). Carbon dioxide and intergenerational choice. *American Economic Review*, Vol. 72, pp. 251–256.

Dowlatabadi, H. & Morgan, M. G. (1993). A model framework for integrated studies of the climate problem. *Energy Policy*, pp. 209–221.

Elzen, den, M. G. J. (1993). Global Environmental Change: an Integrated Modelling Approach. Ph.D. thesis, Van Arkel Publishers, Utrecht, The Netherlands.

Elzen, den, M. G. J. & Rotmans, J. (1993). Modelling Global Biogeochemical Cycles: an Integrated Modelling Approach. RIVM Report no. 461502003, Bilthoven, The Netherlands.

IPCC (Intergovernmental Panel on Climate Change) (1991). *Climate Change: The IPCC Response Strategies*. Island Press.

IPCC (Intergovernmental Panel on Climate Change) (1992). *Climate Change* 1992: *The Supplementary Report to the IPCC Scientific Assessment*. J. T. Houghton, B. A. Callander and S. K. Varney (Eds). Cambridge University Press.

Janssen, M. A., Elzen, den, M. G. J. & Rotmans, J. (1992). Allocating CO_2-Emissions by Using Equity Rules and Optimization. RIVM Report no. 222901012, Bilthoven, The Netherlands.

Meadows, D. L., Behrens III, W. W., Meadows, D. H., Naill, R. F., Randers, J. & Zahn, E. K. O. (1974). *Dynamics of Growth in a Finite World*. Cambridge, MA: Wright-Allen Press, Inc.

Nordhaus, W. D. (1992). An Optimal Transition Path for Controlling Greenhouse Gases. *Science*, Vol. 258, pp. 1315–1319.

Nordhaus, W. D. (1993). Rolling the 'DICE': an optimal transition path for controlling greenhouse gases. *Resource and Energy Economics*, Vol. 15, pp. 27–50.

Press, W. H., Flannery, B. P., Teukolsky, S. A. & Vetterling, W. T. (1988). *Numerical Recipes in C: The Art of Scientific Computing*. Cambridge University Press.

Ramanathan, V., Lian, M. S. & Cess, R. D. (1979). Increased atmospheric CO_2: zonal and temperature. *Journal of Geophysical Research*, Vol. 84, pp. 4949–4958.

Rinnooy Kan, A. H. G. & Timmer, G. T. (1989). Global Optimizing. In G. L. Nemhauser, A. H. G. Rinnooy Kan and M. J. Todd (Eds) *Handbooks in Operation Research and Management Science Volume 1: Optimization*. Amsterdam: North-Holland.

Rotmans, J. (1990). IMAGE: An Integrated Model to Assess the Greenhouse Effect. Ph.D. thesis, Dordrecht: Kluwer Academic.

Rotmans, M., Hulme & Downing, T. (1994a). Climate Implications for Europe: an Application of the ESCAPE Model. *Global Environmental Change*, Vol. 4, pp. 97–124.

Rotmans, J., Asselt, van, M. B. A., Bruin, de, A. J., Elzen, den, M. G. J., Greef, de, J., Hilderink, H., Hoekstra, A. Y., Janssen, M. A., Köster, Martens, W. J. M., Niessen, L. W. & Vries, de, H. J. M. (1994b). Global Change and Sustainable Development: a Modelling Perspective for the Next Decade. RIVM Report no. 461502004, Bilthoven, The Netherlands.

Tahvonen, O., Von Storch, H. & Von Storch, J. (1993). *Economic Efficiency of CO_2 Reduction Programs*. Max-Planck-Institut für Meteorologie, Report No. 105, Hamburg, May 1993, ISSN 0937-1060.

UN (1992). Agenda 21. United Nations Conference on Environment and Development, Rio de Janeiro, June 1992.

Vries, de, H. J. M., Fiddaman, T. & Janssen, R. (1993). Outline for a Global Environmental Strategic Planning Exercise. RIVM Report no. 461502002, Bilthoven, The Netherlands.

Wigley, T. M. L., Holt, T & Raper, S. C. B. (1991). *STUGE: an Interactive Greenhouse Model: Users Manual*. Norwich: Climatic Research Unit.

APPENDIX: REDUCED VERSION OF THE CLIMATE CHANGE MODEL

The reduced version of the simulation model is based on equations of the simulation model itself (Elzen, 1993) and represents the core of the model designed to estimate the global mean temperature change. The variables of the climate change model, which are treated as exogenous variables in the reduced version, are not very sensitive to changes in the carbon tax policy in a subdomain of the solution space. The values of these exogenous variables are updated several times during the optimization to derive a solution that is consistent with the simulation model.

The atmospheric CO_2 concentration is determined by fossil fuel combustion, flux of CO_2 from the terrestrial biota, uptake of CO_2 by the oceans and the net ecosystem production flux, and can be modelled according to the following equation (A.1) (Rotmans, 1990). The fluxes *NFSEM*, *FOVS*, and *TNEP* are treated as exogenous variables in the reduced version. Within the simulation model, they are related to a number of processes:

$$\frac{\mathrm{d}pCO_2(t)}{\mathrm{d}t} = atmcf(FSEM(t) + NFSEM(t) - FOVS(t) - TNEP(t)), \tag{A.1}$$

where:

pCO_2 = atmospheric CO_2 concentration (ppmv);
$atmcf$ = factor that converts emissions of CO_2 into concentrations (= 0.471 ppmv/GtC);
$FSEM$ = fossil fuel combustion flux (GtC/yr);
$NFSEM$ = non-fossil carbon flux of CO_2 due to human disturbance (GtC/yr);
$FOVS$ = flux from the atmosphere to oceanic mixed layers (GtC/yr);
$TNEP$ = carbon flux by total net ecosystem production (GtC/yr).

Changes in the radiative forcing of the climate system, ΔQ are caused by changes in the concentration of radiative active trace gases. According to Ramanathan *et al.* (1979) the following relation approximately holds for the change in the radiative forcing by CO_2 emissions:

$$\Delta Q_{CO_2}(t) = \left(\frac{\Delta Q_{2\times CO_2}}{\ln(2)}\right)\ln\left(\frac{pCO_2(t)}{pCO_{2,in}}\right), \tag{A.2}$$

where:

ΔQ_{CO_2} = change in radiative forcing by CO_2 (W/m^2);
$\Delta Q_{2\times CO_2}$ = radiative forcing for a doubled CO_2 concentration (equal to 4.3 W/m^2);
$pCO_{2,in}$ = initial CO_2 concentration (294.0 ppmv).

The total change in radiative forcing can be written as:

$$\Delta Q(t) = \Delta Q_{CO_2}(t) + \Delta Q_{nonCO_2}(t). \tag{A.3}$$

Besides the radiative forcing of other greenhouse gases, the exogenous variable ΔQ_{nonCO_2} also incorporates the feedbacks of sulphur and stratospheric ozone depletion.

The change in temperature of the ocean mixed layer ΔT_o is related to this radiative forcing in the equation

$$\frac{\mathrm{d}\Delta T_o(t)}{\mathrm{d}t} = \frac{\Delta Q(t) - \lambda\Delta T_o(t) - \Delta F(t)}{C_m}, \tag{A.4}$$

where:

λ = climate sensitivity parameter (is 1.72 W/m^2 °C);
ΔF = change in heat flux at the bottom of the mixed layers (W/m^2);
C_m = bulk heat capacity of the ocean mixed layer (is 10.97 Wy/m^2 °C).

In equilibrium, supposing an instantaneous response of global temperature to external radiative forcing, the temperature change can be formulated as:

$$\Delta T_{eq}(t) = \frac{\Delta Q(t)}{\lambda}. \tag{A.5}$$

The temperature change of the atmosphere over land can then be calculated. Assuming that the temperature change of the atmosphere over the ocean equals the temperature change in the mixed ocean layer, the surface-air temperature change can be expressed as:

$$\Delta T(t) = \frac{f\lambda \Delta T_{eq}(t) + k\Delta T_o(t)}{f\lambda + k}, \tag{A.6}$$

where:

ΔT = change in surface-air temperature (°C);
f = fraction of the globe covered by land;
k = coefficient that represents the heat transfer between land and ocean.

Variables which are used as exogenous variables in the optimization approach are therefore *NFSEM*, *FOVS*, *TNEP*, ΔQ_{nonCO_2} and ΔF. Note: *FSEM* is an output of the energy model.