

Modeling of CO₂ Reduction Impacts on Energy Prices with Modelica

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Abstract

There is growing evidence that anthropogenic carbon dioxide (CO₂) emissions as a by-product of the combustion of fossil fuels for energy use is raising the earth's temperatures and potentially leading to irreversible climate change. Additionally the growth in global emissions is likely to rise at an increasing rate due economic growth, especially in developing countries. Leading climate change mitigation strategies require a global CO₂ emission permit trading regime which is postulated to facilitate the lowest cost emission reduction options and technologies. However, given the technologies are still maturing the economic considerations appear to dictate slow initial reductions which will then grow at an increasing rate as technologies such as wind, solar and carbon capture and storage mature. These economic considerations however may be in conflict with longer-term optimization of costs and benefits, which may be better addressed by earlier intervention. In this paper we present a Modelica model designed to allow exploration of the tradeoffs between least cost emission cuts and early stabilization of atmospheric carbon dioxide.

1 Introduction

The energy and climate systems are now intimately bound through human activity. The evidence that anthropogenic carbon dioxide (CO₂) emissions as a by-product of the combustion of fossil fuels for energy use is raising the earth's temperatures and potentially leading to irreversible climate change [6]. Additionally the growth in global emissions is forecast to rise rapidly due to economic growth, especially in developing countries. In order to minimize the impacts of rising emissions on global temperatures and potentially catastrophic events such as multi-metre sea level rises deep cuts are required early [5,16].

The leading climate change mitigation strategies require a global CO₂ emission permit trading regime which is postulated to facilitate the lowest cost emission reduction options and technologies. However, given the technologies are still maturing the economic considerations appear to dictate slow initial reductions which will then grow at an increasing rate as technologies such as wind, solar and carbon capture and storage mature.

A significant question in the politics of climate change has been the trade-off between the costs of mitigation versus the costs of doing nothing. What is missing is a model quantifying the costs and benefits of the rate of of mitigation, taking into account that early strategies may be less efficient than later ones, yet have more value for mitigation if it is accepted that early mitigation is better than late mitigation, since effects accumulate.

The leading climate change mitigation strategies require a global CO₂ emission permit trading regime which is postulated to facilitate the lowest cost emission reduction options and technologies. This kind of scheme has its origin in earlier approaches to emissions reduction, such as the US Acid Rain Program, initiated by the Clean Air Act of 1990 [17], with the underlying theory of artificial markets being created to correct for market failures dating back to the late 1960s [18].

Given that the technologies are still maturing, the economic considerations appear to dictate slow initial reductions which will then grow at an increasing rate as technologies such as wind, solar and carbon capture and storage mature – hence the need not only to create an artificial market, but to explore how to use price as an instrument to drive change at the appropriate rate.

In this paper we present a Modelica model which explores the tradeoffs between least cost emission cuts and early stabilization of atmospheric carbon dioxide.

1.1 Model assumptions

1.2 The climate system

The climate model allows for either linear or exponential growth in emissions and in atmospheric carbon dioxide; current trends look linear but exponential growth may occur in the worst case if growth in energy use tracks population growth. As a first approximation, although there are indications that environmental sinks may saturate [7], we assume a fixed ratio of natural CO₂ sinks (plants, land, ocean) to emissions. This assumption is reasonable if abatement measures are effective (changes in the ocean in particular can be rapid [8]), i.e., this is a conservative assumption for the benefits of early abatement.

Our climate model assumes the following parameters:

- We assume all variation in greenhouse cases, at a first approximation, is in CO₂ (reasonable since methane outputs have stabilized since 1990, and CO₂ output is the largest single anthropogenic contributor to greenhouse gases [10]) and therefore work with gigatonnes CO₂-equivalent (GtCO₂-eq)
- We base our scenarios on the IPCC's, which vary total emissions increases from 2000 to 2030 from 9.7 GtCO₂-eq to 36.7 GtCO₂-eq off a baseline of 39.8 GtCO₂-eq, prior to mitigation [11]
- Total sinks including oceans and land-based consumers of CO₂: 50% of anthropogenic CO₂ production (30% oceans, 20% land) [9]

Our starting point is the scenarios defined by the Intergovernmental Panel on Climate Change (IPCC) [12]. These scenarios are intended to illustrate a range of possibilities, without attempting to predict the likelihood of any one outcome [13]. Any of these scenarios could equally well be modeled and for completeness all should be modeled. However, for purposes of illustrating the use of Modelica, we focus here on using only one base scenario, and vary mitigation strategy assuming a given trend in energy demand. Specifically, we choose the A1C scenario, because that represents high growth with maximal convergence of developing economies with developed economies. This scenario combination is relevant because of the debate as to whether mitigation implies forcing unremitting poverty on developing countries [14,15].

1.3 Structure of Paper

The remainder of this paper is structured as follows. In Section 2, we develop a model, based on plausible parameters, In Section 3, we present examine outputs of the model, and discuss future applications. Finally, Section 4 concludes with an overall discussion of findings and proposals for future work.

2 The Model

2.1 Methodology and assumptions

- We assume that the system is continuous since all physical process are continuous and the abatement and economic changes happen slowly
- Assume that the influence of abatement paths impacts only the cost of abatement represented by the carbon price. We don't model the feedback in the other direction
- Assume that 50% of emissions are absorbed environmentally

2.2 The economics of abatement

We develop a simple model based on the technology assessments of McKinsey and Co.'s climate change mitigation team in Sweden [19,20]. This model includes a cost curve for marginal abatement integrated with a mean reverting model for global energy prices.

- Assume that costs reduce over time as learning occurs
 - constant learning rates for efficiency of energy production and use
- There are two ways to reduce emissions:
 - efficiency-based which reduces total energy produce to meet same "virtual demand"
 - increase proportion of zero-CO₂ energy
- Underlying energy price remains constant and is increased only through carbon pricing (likely to be incorrect as supply fails to keep up with demand, e.g., as appears to be happening at time of writing with oil).

2.3 Model design

The continuous assumption allows use to use ordinary coupled differential equations (ODEs).

Data from IPCC converted to rates of emission change and energy production/efficiency change and are incorporated as growth parameters in ODEs.

The most significant equations are:

- 1) $U'(t) = E(t) \times U(t) + L$
- 2) $P_E'(t) = P_{E-MRR} \times (P_{LT} + P_C \times C_{BI} - P_E)$
- 3) $P_C'(t) = P_{C-MRR} \times (P_A - P_C)$

Equation (1) allows us to express energy use U as an exponential component E and a linear component L . U represents virtual energy as explained above: it is the trend in energy demand, not taking into account that actual energy use may be less owing to efficiency gains. In our examples in this paper, we hold E to zero.

Equation (2) captures the variation in energy price (P_E) in terms of the energy price mean reversion rate (P_{E-MRR}) which captures the tendency for price spikes to smooth out, long term energy price (P_{LT}), the modeled carbon price (P_C), the carbon intensity at the start of the modeled time (C_B).

Equation (3) models the trend in carbon price in terms of the carbon price mean reversion rate (P_{C-MRR}) and abatement cost (P_A).

This is a closed form model for the interaction between energy costs under a carbon pricing regime and the concentration of carbon dioxide in the atmosphere.

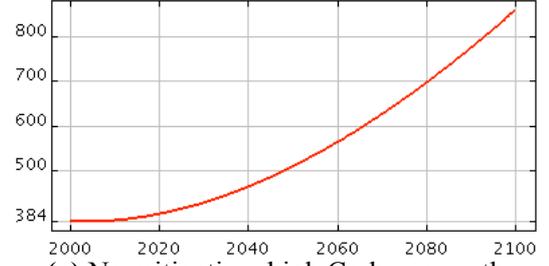
These equations can be expressed in Modelica as follows:

```

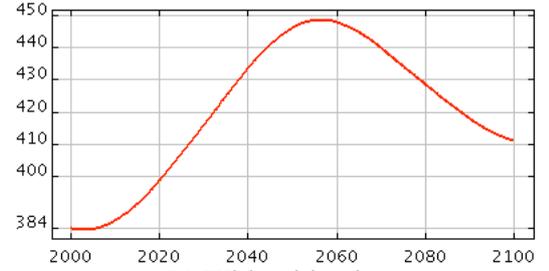
der(energyUse) = // (1)
    energyGrowthExp * energyUse +
    energyGrowthLinear;
der(energyPrice) = // (2)
    energyPriceMRR *
    (longTermEnergyPrice +
    carbonPrice * baseCarbonIntensity -
    energyPrice);
der(carbonPrice) = // (3)
    carbonPriceMRR * (abatementCost -
    carbonPrice);

```

This model is provided as a starting point, so the parameters should be taken as examples. Given that the IPCC has deliberately not provided probabilities for their scenarios [12], in the same spirit we do not claim that our specific examples are predictions, but rather case studies on which predictions can be built, once it



(a) No mitigation, high Carbon growth



(b) With mitigation

Figure 1. CO₂ concentration

becomes clearer which scenarios are most likely.

3 Results

We have run some variations on parameters through the model, to illustrate how scenarios can be explored.

The A1C scenario explored here in its worst case with no mitigation results in rapid growth in carbon emissions, resulting in atmospheric CO₂ of the order of 800 parts per million (ppm), as illustrated in Figure 1(a). In this scenario, most energy by 2100 is carbon-based, as we have assumed zero mitigation: no increase in efficiency, no increase in non-emitting energy sources. With mitigation CO₂, peaks at around 450ppm (Figure 1(b) illustrates the early mitigation strategy; the late mitigation strategy is similar with a slightly higher, later peak).

Our mitigation strategy is based on reducing emissions to those of the BIT IPCC scenario. The early mitigation and late mitigation strategies are based on assuming the same cumulative reduction in emissions, but reversing the order, with faster change earlier in the more aggressive scenario.

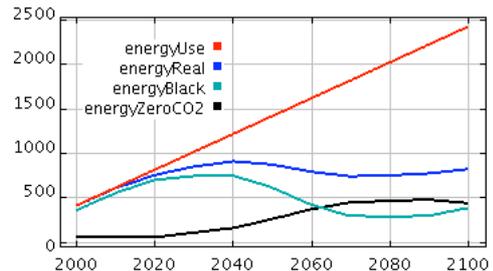
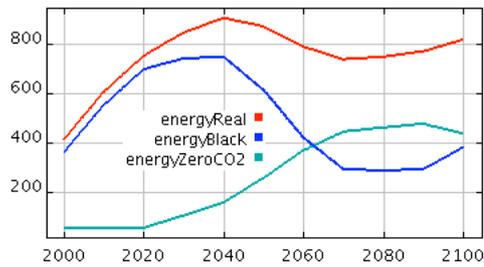
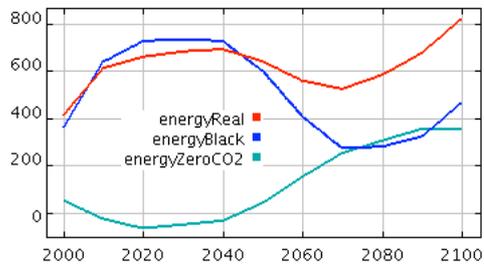


Figure 2. Energy Pattern (late mitigation)



(a) Less aggressive strategy



(b) More aggressive strategy.

Figure 3. “Real” Energy Pattern

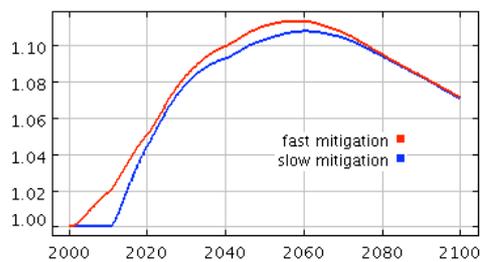


Figure 4. Energy cost relative to no mitigation

Figure 2 illustrates the change in energy pattern with our late mitigation (less aggressive) strategy. In this scenario, an abatement strategy has already started in 2000, and increases up to 2060, when new measures start to ease off. In the meantime efficiency measures increase up to 2050. In graphs, *energyUse* means “virtual” energy demand (energy demand not taking into account reductions caused by efficiency), *energyReal* is actual energy demand, allowing for efficiency measures, *energyBlack* is energy resulting in carbon emissions, and *energyZeroCO2* is emission-free energy.

Figure 3 contrasts the less aggressive (a) and more aggressive (b) strategies, this time leaving out the “virtual” energy line, since it is the same in all cases. Required non-emitting energy goes below zero in (b) because we are more than meeting the emission target in early years without adding more zero-emission energy, by aggressive efficiency measures. This is a flaw in the model, since we should not force abatement costs to be higher for more mitigation than is actually needed.

When we compare costs, the two mitigation strategies come out approximately equal – in the end. As illustrated in Figure 4 (cost scaled to no mitigation = 1), the fast mitigation strategy results in higher

energy costs in the interim. However, the following limitations in the model favour the late mitigation strategy and therefore make it appear the better strategy in terms of cost:

- The constant learning rate assumption biases the simulation towards lower costs for late mitigation, as new technologies are more efficient, later
 - in practice, an aggressive mitigation strategy is likely to increase the learning rate e.g. if carbon taxes are passed through to low emission R&D
- Extra costs of late mitigation to the environment are not factored in, especially if environmental sequestration becomes less efficient as CO₂ levels rise
- Extra costs of early decommissioning of polluting plant would be higher in a late mitigation strategy, as a higher fraction of such plant would be built later in the strategy

We should however note that even where the faster mitigation strategy is more expensive, the gap is not large (at most 2%), owing to the fact that efficiency strategies are included in the mix.

4 Conclusions

This model provides a starting point for evaluating abatement paths for bringing CO₂ levels into line with requirements for stabilizing climate change.

We have modeled a limited range of scenarios to illustrate the techniques. Once it becomes clearer which scenarios are more probable, it will be a simple matter to rerun the model with different parameters.

In our future work we will investigate a wider range of scenarios, and fine-tune the model for a better fit to the real world, for example, changes in environmental sequestration as CO₂ levels rise. We will also fine-tune economic assumptions, to allow for a range of policy options such as more aggressive support for R&D for low-emissions technologies, and carbon taxes.

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References

- [1] Peter Fritzon, Peter Aronsson, Håkan Lundvall, Kaj Nyström, Adrian Pop, Levon Saldamli, David Broman. The OpenModelica Modeling, Simulation, and Development Environment. In *Proceedings of the 46th Conference on Simulation and Modelling of the Scandinavian Simulation Society (SIMS2005)*, Trondheim, Norway, October 13-14, 2005.
<http://www.ida.liu.se/projects/OpenModelica>
- [2] Peter Fritzon. *Principles of Object-Oriented Modeling and Simulation with Modelica 2.1*, 940 pp., ISBN 0-471-471631, Wiley-IEEE Press, 2004.
- [3] The Modelica Association. The Modelica Language Specification Version 3.0, Sept 2007.
<http://www.modelica.org>.
- [4] Peter Fritzon et al. The OpenModelica Users Guide, July 2007.
<http://www.ida.liu.se/projects/OpenModelica>.
- [5] JE Hansen. Scientific reticence and sea level rise, *Environ. Res. Lett.*, vol. 2 no. 2 April-June 2007
- [6] GC Hegerl and FW Zwiers and P Braconnot and NP Gillett and Y Luo and JA Marengo Orsini and N Nicholls and JE Penner and PA Stott, Chapter 9: Understanding and Attributing Climate Change. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (ed. S Solomon and D Qin and M Manning and Z Chen and M Marquis and KB Avery and M Tignor and HL Miller, pages 663-745, Cambridge University Press 2007
- [7] Peter M. Cox, Richard A. Betts, Chris D. Jones, Steven A. Spall and Ian J. Totterdel. Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model, *Nature* vol. 408, 9 November 2000, pp 184-187
- [8] John E. Dore, Roger Lukas, Daniel W. Sadler and David M. Karl. Climate-driven changes to the atmospheric CO₂ sink in the subtropical North Pacific Ocean, *Nature* vol. 424, 14 August 2003 pp 754-757
- [9] Richard A. Feely, Christopher L. Sabine, Kitack Lee, Will Berelson, Joanie Kleypas, Victoria J. Fabry and Frank J. Millero. Impact of Anthropogenic CO₂ on the CaCO₃ System in the Oceans, *Science* 16 July 2004: Vol. 305. no. 5682, pp. 362 – 366
- [10] IPCC, 2007: Summary for Policymakers. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- [11] IPCC, 2007: Summary for Policymakers. In: *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- [12] Nebojsa Nakicenovic, Joseph Alcamo, Gerald Davis, Bert de Vries, Joergen Fenhann, Stuart Gaffin, Kenneth Gregory, Arnulf Grubler, Tae Yong Jung, Tom Kram, Emilio Lebre La Rovere, Laurie Michaelis, Shunsuke Mori, Tsuneyuki Morita, William Pepper, Hugh Pitcher, Lynn Price, Keywan Riahi, Alexander Roehrl, Hans-Holger Rogner, Alexei Sankovski, Michael Schlesinger, Priyadarshi Shukla, Steven Smith, Robert Swart, Sascha van Rooijen, Nadejda Victor, Zhou Dadi. *IPCC Special Report on Emissions Scenarios (SRES): Special Report on Emissions Scenarios, Working Group III, Intergovernmental Panel on Climate Change (IPCC)*, Cambridge University Press, Cambridge, 2000.
<http://www.grida.no/climate/ipcc/emission/index.htm>
- [13] Nebojsa Nakicenovic, Arnulf Grubler, Stuart Gaffin, Tae Tong Jung, Tom Kram, Tsuneyuki Morita, Hugh Pitcher, Keywan Riahi, Michael Schlesinger, P. R. Shukla, Detlef van Vuuren, Ged Davis, Laurie Michaelis, Rob Swart and Nadja Victor. IPCC SRES Revisited: A Response, *Energy & Environment*, vol. 14, nos. 2 & 3, 2003, pp 187-214.
- [14] Olive Heffernan. A push for political will, *Nature Reports Climate Change*, vol. 6 Nov 2007 p 79.
<http://www.nature.com/climate/2007/0711/pdf/climate.2007.60.pdf>
- [15] *Up in smoke? Threats from, and responses to, the impact of global warming on human development*, New Economics Foundation, London, 2004,
<http://www.neweconomics.org/gen/uploads/igeebque013nvy455whn42vs19102004202736.pdf>
- [16] J. Hansen, Mki. Sato, P. Kharecha, G. Russell, D.W. Lea, and M. Siddall. Climate change and

trace gases. *Phil. Trans. Royal. Soc. A*, vol. 365, 2007, pp 1925-1954, doi:10.1098/rsta.2007.2052

- [17] Clean Air Act, US Government, 1990
- [18] W.D. Montgomery, Markets in Licenses and Efficient Pollution Control Programs, *Journal of Economic Theory* 5 (Dec 1972):395-418
- [19] Per-Anders Enkvist, Tomas Nauc ler and Jerker Rosander. A cost curve for greenhouse gas reduction, *The McKinsey Quarterly*, no. 1 2007, pp 35-45
- [20] Diana Farrell, Scott S. Nyquist and Matthew C. Rogers. *Curbing the growth of global energy demand*, The McKinsey Quarterly Web exclusive, 12 pp, July 2007

Appendix – The Complete Model

```

class CarbonWorldXIIa

    parameter Integer scenario=1 "1 for faster
    early abatement, to 2 for slow early
    abatement or 3 for 0 abatement";

    parameter Real gamma = 0.006725 "Correction
    factor which can be used to account for
    concentration dependent sequestration such as
    sea and bio-";

    parameter Real absorptionFactor = 0.5;

    Real emission(start = baseEmission);
    Real carbConc(start=384)
    "Carbon Concentration";
    Real abatementCO2(start =
startAbatementCO2);
    Real abatementEfficiencyCO2 (start=0);
    Real abatementCO2Imputed;
    Real energyZeroCO2 (start = 0 );
    Real energyEfficiency (start = 0 );
    Real energyReal (start = 0);
    Real abatementCost;
    Real energyPrice(start =
    longTermEnergyPrice);
    Real carbonPrice(start =
    longTermCarbonPrice);
    Real energyUse (start = baseEnergyUse);
    Real energyBlack;
    Real totalCarbonIntensity;
    Real totalCarbonIntensity100;
    Real efficiencyValue(start =
    startEfficiencyValue);
    parameter Integer abateCO2 = 1,
    efficiencyEnergy = 2, abateEfficiency = 3;
    Real abatementStepsCO2(start =
    plans[1, scenario, abateCO2]);
    Real efficiencyStepsEnergy (start =
    plans[1, scenario, efficiencyEnergy]),
    Real abatementStepsEfficiency(start =
    plans[1, scenario, abateEfficiency]);

    parameter Real plans[:, :, :] = {
    {{0.22, 0.69, 0.2},{0, 0, 0.76},{0, 0,

```

```

0}},
    {{0.22, 0.69, 0.2},{0, 0, 0.76},{0, 0,
0}},
    {{0.57, 5.33, 0.56},{0.72, 15.23, 1.11},
{0, 0, 0}},
    {{1.07, 10.64, 0.58},{1.01, 17.76, 0.86},
{0, 0, 0}},
    {{1.16, 14.02, 0.65},{0.99, 19.04, 0.83},
{0, 0, 0}},
    {{1.69, 23.47, 0.72},{1.52, 25.11, 0.78},
{0, 0, 0}},
    {{1.84, 28.18, 0.76},{1.84, 28.18, 0.76},
{0, 0, 0}},
    {{1.52, 25.11, 0.78},{1.69, 23.47, 0.72},
{0, 0, 0}},
    {{0.99, 19.04, 0.83},{1.16, 14.02,
0.65},{0, 0, 0}},
    {{1.01, 17.76, 0.86},{1.07, 10.64,
0.58},{0, 0, 0}},
    {{0.72, 15.23, 1.11},{0.57, 5.33,
0.56},{0, 0, 0}},
    {{0, 0, 0.76},{0.22, 0.69, 0.2},{0, 0,
0}}
};

```

```

parameter Real abatementCatchupRate=1 "From
final abatementPlan to end of sim";

```

```

parameter Real energyGrowthExp=0.0,
energyGrowthLinear=20.0/(GJ_MWh/energyConvFac
tor);

```

```

parameter Real tonnesToPPM =0.127365 "from
H:-aliebman-My Research-Energy-Climate
Change-Emissions trading-AL - Carbon Trading
Research-Modelica Models-
CalibrationData.xls";

```

```

parameter Real carbonToCO2 = 3.664
"Conversion between mass Carbon and Carbon
Dioxide";

```

```

parameter Real startEfficiencyValue= 31.06
"150 $/tCO2e";

```

```

parameter Real startAbatementCO2=5 "tCO2e";

```

```

parameter Real learningRate=0.02;

```

```

parameter Real GJ_MWh=3.6,
energyConvFactor=GJ_MWh "GJ_MWh or 1.0";

```

```

parameter Real baseEmission=40 "40 GtCO2e
from energy sector - McKinsey", baseEnergyUse
= 411*energyConvFactor/GJ_MWh "IPCC Special
Report on Emission Scenario (SRES) 2000 -
linear fit and interpolation between 1990-
2050 ";

```

```

parameter Real baseCarbonIntensity =
baseEmission /baseEnergyUse "0.7
/energyConvFactor - tonnes/MWh converted to
tonnes/GJ";

```

```

parameter Real carbonPassThrough = 1;

```

```

parameter Real longTermEnergyPrice = 80
/energyConvFactor; //"100/MWh long term
energy price" // Will need to be a dynamic
quantity later

```

```

parameter Real longTermCarbonPrice = 0.0;
// "$20/tCO2 long term abatement /carbon
cost" // Need to check this actually makes
sense!

```

```

parameter Real energyPriceMRR = 1.0 "Energy
price mean reversion rate";

```

```

parameter Real carbonPriceMRR = 1.0 "Carbon
Price mean reversion rate" ;

```

```

Real relEnergyPrice (start = 1);
Real energyCostTrend (start = 1);
Real scaledEnergyPrice (start=0);

```

```

Integer which (start = 2); // used which =
1 to initialize abatements

function nextStep
  input Real data[:, :, :];
  input Integer i, j, k;
  output Real step;
algorithm
  step := data[i, j, k];
end nextStep;

equation
  energyCostTrend = relEnergyPrice *
energyUse / baseEnergyUse;
  // useful to compare strategies on cost
  relEnergyPrice = energyPrice /
longTermEnergyPrice;
  // useful to compare energy cost across
strategies that vary total use
  scaledEnergyPrice = relEnergyPrice *
energyReal / energyUse;
  abatementCost =
efficiencyValue*(sqrt(abatementCO2/startAbate
mentCO2) - 1);
  der(efficiencyValue) = -
learningRate*efficiencyValue " -
longTermEnergyPrice *
someKindOfCarbonIntensity";

  when sample(0, 10) then //StartTime
    which = if pre(which) < size(plans, 1)
then
    pre(which) + 1 else pre(which);
  end when;

  abatementStepsCO2 = nextStep (plans, which,
scenario, abateCO2);
  efficiencyStepsEnergy = nextStep(plans,
which, scenario, efficiencyEnergy);
  abatementStepsEffciency = nextStep(plans,
which, scenario, abateEffciency);

  der(abatementCO2) = abatementStepsCO2; //
This is a carbon dioxide quantity

  der(energyEfficiency) =
efficiencyStepsEnergy*energyConvFactor/GJ_MWh
; // This is an energy quantity

  der(abatementEfficiencyCO2) =
abatementStepsEffciency; // This is a
carbon dioxide quantity

  energyZeroCO2=(abatementCO2-
abatementEfficiencyCO2)/baseCarbonIntensity;
  energyBlack = energyUse - energyEfficiency-
energyZeroCO2;
  emission = energyBlack*baseCarbonIntensity;

abatementCO2Imputed=energyZeroCO2*baseCarbonI
ntensity;

  totalCarbonIntensity = emission/energyUse;
  der(carbConc) =
tonnesToPPM*(emission*absorptionFactor)-
gamma*carbConc;

  der(energyUse) =
energyGrowthExp*energyUse+energyGrowthLinear;
  der(energyPrice) = energyPriceMRR*(
longTermEnergyPrice +
carbonPrice*carbonPassThrough*
baseCarbonIntensity - energyPrice);
  der(carbonPrice) =
carbonPriceMRR*(abatementCost -
carbonPrice);
  totalCarbonIntensity100=
100*totalCarbonIntensity;
  energyReal = energyBlack + energyZeroCO2;
end CarbonWorldXIa;

```